Political Platforms: Technology, User Affordances, and Campaign Communications

by

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Dedication

This dissertation is dedicated to my parents, who made all of this possible.

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Abstract

Political candidates communicate across a wide number of platforms during their campaigns, including television, Facebook, Twitter, debates, radio, and newspapers. However, these platforms are not the same. Each is made up of a number of different technical features and user affordances. Technical features shape the type of content that can be transmitted through each platform and user affordances describe how platforms are interpreted and used by candidates. The interaction between features and affordances suggests that content ought to vary across platforms, even when the user of those platforms is the same.

I argue in this project that the interaction of features and affordances inclines platforms towards certain ideological audiences and allows for interactions between candidates. I term these the audience and channel of the platform. Audience can range from *narrow* to *broad* indicating the degree to which the audience is ideologically homogenous. Channel goes from *shared* to *independent* as an indication of how easily candidates can directly interact with their opponents.

I find that *broad* audience platforms with *independent* channels are, on average, more negative than *narrow* audience, *shared* channel platforms. I also find that policy content is more present in *broad* audience platforms. Finally, I find that visual communications also exhibit similar patterns. *Broad* audience and *independent* channel platforms are markedly more negative and contain more policy language than *narrow* audience and *shared* channel platforms. These findings stand up with multiple test of robustness, including different dictionary specifications, word counts, and different elections.

These findings suggest that audiences are being exposed to systematically different content, depending on where they get their information from. This could have meaningful and serious implications for our understanding of political knowledge, polarization, candidate evaluations, and voting. I offer the Platform Audience and Channel Theory as a tool for researchers to study current platforms and a way to understand platforms that have not yet been developed.

Chapter 1 Political Platforms

A classic example of the impact that communication platforms can have on individual political preferences is the September 1960 Kennedy-Nixon debate. Nixon held a small lead over Kennedy in the polls in the days before the event. During the debate itself, Nixon refused to wear stage makeup and appeared ill and pale, in comparison to a tanned and healthy-looking Kennedy. The live visual representation of the two candidates – which had not existed as a technical capacity of either newspaper or radio content – turned out to be meaningful to the election. Political pundits relying on the televised debate generally concurred that Kennedy had won; those who listened to the event on the radio evaluated Nixon as having given the stronger performance. Evaluations of the candidates thus depended on the platform by which one experienced the debate (Druckman, 2003). Television added new (visual) information – information that may have fundamentally altered citizens' evaluations of the candidates, tightening what would ultimately be a close and consequential election.

Changes in communication technology clearly mattered in the 1960 campaign, and they continue to matter now. The type of information available through television produced a massive shift in the information voters had access to; similar shifts have occurred as a result of internet-based journalism, Twitter, and Facebook. This project consequently seeks to understand how political campaign information varies across platforms, by assembling and exploring the largest-ever database of multi-platform campaign communication.

There is very little accumulated knowledge as to how content may vary by platforms. To a certain degree, then, the work that follows is descriptive and inductive. But my approach is partly deductive as well. Informed by the impact of the Kennedy-Nixon debate, and the growing bodies of scholarship on campaign communication, media technology, platforms and affordances, I develop a theory of communication platforms as they relate to political campaigning: the Platform Audiences and Channel Theory (PACT). The PACT leads to testable hypotheses about the tone and substance of campaign content across platforms. Testing these hypotheses adds not just to what we know about campaigns in the current technological context, but also sets up some expectations about how campaigns may look as technologies change in the future.

This work responds to recent concerns about a lack of understanding about how campaigning plays out across multiple platforms (Kreiss et al., 2017; Bossetta, 2018; Bode & Vraga, 2018). There is good scholarship focused on single platforms, of course; and the insights of that work will be crucial to the ideas developed below. It is however vital that research both directly compare results across platforms and move beyond the platforms that are most easy to scrape (Twitter). Moreover, research must try to think beyond current platforms, and consider more broadly the ways in which features and affordances of platforms matter for political communication. Doing so increases the likelihood that theories will not be time-bound, connected to the platforms that currently exist but inevitably change – or are replaced – over time. The development of a durable theory of platform effects is thus one major objective of the work that follows. So too is the consideration of platforms as part of a larger communication ecosystem. We have evidence that campaigns think of platforms this way; that is to say, they view them as separate entities, with different strengths and weaknesses, complementing each other as part of a broader communication environment. It is time for research to take a similar view. The PACT is one step in that direction.

The Platform Audience Channel and Theory is based on understanding how platforms are structured. I argue that the content on any given communication platform is a function of the technical features and user affordances; respectively, what the platform can do and what users use it for. For political campaigns, the interaction of features and affordances influences how they view communication platforms. The relevant dimensions are how politically homogeneous the audience of the platform and the degree to which candidates must interact with one another. I refer to these as the audience and channel of the platform and are the underlying theoretical foundations of PACT. I argue that differences in audience and channel influence the content across platforms and look at a single campaign cycle to test differences in content across a range of communication platforms.

I focus on the 2016 US presidential campaign by collecting content from a wide and diverse set of platforms, including television ads, debate transcripts, speeches, Facebook posts, Twitter content, and Instagram images. I use these data to look at both sentiment and policy substance in the content of political campaign communications. There are likely a number of different kinds of politically relevant content which one could look at, but both sentiment and policy content have, perhaps some of the most, important political implications.

Sentiment, for instance, has been linked to user attention, candidate evaluations, and behavioral implications. This is especially notable for negativity, which may play a vital role in how individuals consume information. Policy language also occupies and important position in political communication. Policy cues have been tied to political knowledge and the ability for citizens to hold governments accountable through updating their understanding of current affairs.

The first set of analyses looks at the tone of each platform's content. I predict that *broad* audience and *independent* channel platforms will be, on average, more negative than *narrow* audience and *shared* channel platforms. I test this by using the Lexicoder Sentiment Dictionary across the entire corpus and I find that television ads (a *broad* and *independent* channel platform) is statistically more negative than Facebook posts and tweets. (both *narrow* and *shared*). These findings indicate that television ads may be the platform that is best able to drive user attention through its use of negativity.

I also predict that *broad* audience platforms will contain more policy language than *narrow* audience platforms. I use a dictionary of policy words and find that *broad* audience platforms, such as television ads and debates, contain policy language in a higher proportion of their content than *narrow* platforms, like Facebook, Twitter, and speeches. This suggests that viewers of television ads and debates are systematically exposed to more policy information than users of other platforms. I also find that negativity and policy language covary on almost all platforms, indicating that policy language is often accompanied by a more negative tone.

Finally, I look at visual communications by comparing Instagram content and television ads using human coders on MTurk. This is important as it allows me to capture non-verbal cues that are not evaluated in dictionary processing. I predict that television will be more negative and have more policy content due to its *broad* nature whereas Instagram will be more positive and have less policy language due to its *narrow* audience. Human responses indicate exactly this relationship. Instagram is statically more positive with less policy content than television ads are.

Results highlight the importance of variations in platforms for the content on them. I find that there are significant differences in the sentiment and substance of campaign communications, in line with expectations from the PACT, and rooted in theories about features and affordances. These findings are robust across multiple specifications of sentiment and substance and supplementary data from historical campaigns and congressional races suggest similar findings as well. This has serious implications for how we understand political information. Campaign information varies systematically across platforms. This does not just mean that campaign information has changed over time; it means that where people get their information is likely to make a fundamental difference to what they are being exposed to.

What I hope to accomplish here is to set out the initial theory and empirical justification for further work using the PACT. This is necessary as the PACT can only be partially tested in this project. There are two reasons. The first is related to the nature of my data: while I have collected a vast body of data from 2016 election, I cannot include all possible platforms, past and future. Functionally, then, the analyses that follow are case studies into 6 different platforms. The resulting analyses provide compelling evidence of my claims; but there are always more platforms that would allow for additional testing of my hypotheses. Second, and more importantly, I develop hypotheses about sentiment and policy content, derived from differences in audiences and channels; but there are myriad other possible differences both in platform features and affordance, and outcome variables, that have yet to be theorized or tested. I see what follows as a critical first step towards testing this newly-developed theory, the PACT. But future work will necessarily focus on additional testing of alternative hypotheses, on more platforms, for more outcome variables.

This dissertation proceeds as follows: Chapter 2 outlines the theoretical justification for the project. It considers in some detail the two primary dimensions across which media platforms vary: technical features and user affordances. Chapter 3 then describes the Platform Audience and Channel Theory and outlines the theory's implications related to the impact of features and affordances on political campaigning. Chapter 4 introduces the data. It lays out the scope of the dataset on the 2016 US presidential election that will be used throughout the rest of the project.

These data capture a wide range of social media, televisions, speeches, and images. I undertake the first analyses in Chapter 5, which looks at systematic differences the sentiment across platforms. Chapter 6 evaluates the presence of policy language and also considers the relationship between tone and policy. Chapter 7 again looks at sentiment and policy but from the perspective of visual communications, such as television ads and Instagram posts. Finally, Chapter 8 closes the project.

Chapter 2 Campaigning Through Platforms

One of the biggest challenges for researchers trying to understand political learning, information exposure, and a bevy of other political communication phenomena is that the media landscape is constantly changing. As modes of communication are continuously developed and adopted, what we might consider "new media" at one moment is rapidly replaced by "newer media" in the next. The primacy of newspapers gave way to radio, which gave way to television, which was soon supplanted by the internet, mobile phones, and onwards. With each new technology came new ways of communicating as well as different types of content. Consider that the development of the radio introduced the broad range transmission of spoken word as a way to get information, as well as breaking news. Information that was previously unavailable to citizens who only had access to newspapers—namely, the sharing of more timely news content—suddenly became available with the advent of radio. This represented a fundamental shift in the nature of the information that individuals were exposed to.

That same shift has been constantly happening throughout history, though. Just as radio represented an introduction of a new form of information because of its technical structure (broadcast voice), so too does every platform. Facebook, for instance, uses social connections and endorsements. In order to know what information is available to citizens, it is vital to consider the underlying structures of communication platforms. Researchers have wrestled with understanding platform effects for some time. Harold Innis, who uses the term "medium of communication" instead of platform, argued that: "a medium of communication has an important influence on the dissemination of knowledge over space and over time and it becomes necessary to study its characteristics in order to appraise its influence in its cultural setting" (Innis, 1951/2008, p. 33). He claimed that mediums of communication privilege either time or space, and that the relative presence of the two has fundamentally shaped cultures throughout history. Innis's basic argument is that platforms (mediums) of communication offer different content depending on their technological form. Radio and television present content based on individualism, materialism, and "news." In contrast, the oral tradition and durable forms of media (i.e., stone engravings, statues and plaques) privilege language, community, and durability.

This claim was echoed and expanded on by Innis's student, Marshall McLuhan, who famously argued that "the medium is the message" (McLuhan, 1994, p. 7). According to McLuhan, mediums are fundamentally different from one another and that differences have implications for how people use and interpret content. As an example, McLuhan argued that the French Revolution was, in part, a function of the spread of printed word and the re-construction of what it means to be French through the content of print media. He contrasts this with the lack of an English Revolution, as the English culture gave primacy to spoken word and common law over written text. To further illustrate his argument, McLuhan points to a study in which participants are exposed to the same content delivered in the same manner across four different platforms and asked to answer questions afterwards. Those who viewed the content on television did significantly better in recollection. However, a follow-up experiment used content that was about the same message but was formatted to fit the traditional way in which those platforms present information. In that study, radio listeners surpassed all other groups in recollection (McLuhan, 1994, p. 311). The point McLuhan is making is that information varies based on the norms of usage on each platform. When information was broadcast in the format that best matches the platform, there were changes in user recall and knowledge retention.

Innis and McLuhan are talking about *biases* of media, such as the bias of the content broadcast on radio to privilege space over time; or the bias of television to use visual and audio cues instead of text. Another way to think about bias is the systematic selection of one set of information over other sets of information. Innis writes about biases as being linked to space or time. This is a useful way of thinking about how scholarship might start to categorize information sources based on their structures and usage and how those may influence biases in content.

Current research has thought about biases as content, producer, and consumption driven. Notable findings suggest that news contains institutional biases (McCombs & Shaw, 1972), partisan biases (e.g. Iyengar & Hahn, 2009), or negativity biases (e.g. Soroka, 2014). There is also a robust field of work on how political campaigns communicate in newspapers and television (e.g., Brians & Wattenberg, 1996); television (e.g., Freedman et al., 2004); Twitter (e.g., Evans et al., 2014); and Facebook (e.g., Williams & Gulati, 2013). While these works and others have shed valuable light on content within platforms, there have been relatively few systematic analyses of content *across* multiple platforms. This project aims to address that gap in the literature by evaluating campaign communication across platforms during the 2016 US presidential election.

It is clear to me that accounting for the differences in content across platforms is crucial to understanding political campaign communication in the modern era. Unfortunately, this is also an area that has been understudied and underdeveloped. Building up a theory for platform dependent constraints can help scholars better understand the communication environment that we exist in. This is not only important for current work and existing platforms but could also help us understand future platforms.

I define a platform as a communication system comprised of technical features and user affordances. Thus, newspapers are a platform as each newspaper is configured in similar ways and relies on similar technology. Facebook is a different platform as users are constrained by a single technical structure. Note that the field is divided as to a definition of platforms. One of the problems may lie in how data is collected, which pushes scholarship into sources of data that are easier to locate and collect, such as Twitter. This leads to an overreliance on those sites, newspapers, or apps to make broad claims about the media ecosystem as a whole. Yet as Segerberg and Bennett note, platforms do not exist in isolation but are also distinct from one another (2011). Further, Thorson and colleagues note that the movement between platforms is noteworthy as a space of analysis for understanding their different constructions and usage (2013). Both pieces point to the need for a broad definition that can handle the complex ways in which platforms exist, change, and are used. Thus, my definition is broad and is purposefully so; and builds on previous work that evaluates platforms. My definition also allows me to draw distinctions between the platforms that are currently in use and is durable enough to account for yet-unreleased platforms.

I propose that there are two relevant dimensions for understanding how platforms shape communication. The first is that platforms are different because of the *technical features* that each platform is made up of. Features are easy to describe: they are simply the "things" a platform has. A newspaper has pictures and text. Radio has audio transmission. Television has video and audio broadcasting. Facebook allows for the uploading of pictures. And so on.

Understanding the features of a platform allows one to understand the structure of information that could be transmitted through a platform.

McLuhan conceptualized information as text, audio, photo, and video. Each platform would contain some combination of these categories and the features of each platform change the presence and weight of each of these forms of information. Yet in the many years since McLuhan was writing, new kinds of information have become available to users of platforms, especially internet-based ones. Social endorsements, liking, sharing, retweeting, etc., are all forms of information that users are exposed to an integrated into their evaluations of content (Messing & Westwood, 2014; Thorson, 2008). Hashtags have altered the ways in which conversations form and spread, and while hashtag usage is primarily thought of as only being part of social media platforms, Donald Trump organized an entire presidential campaign around a hashtag (#MAGA). The point is not that McLuhan was wrong, but that technology has created new forms of information.

This leads to the second dimension of platforms: individuals interact differently with a platform based on their perceptions of what it can be used for. These perceptions are known as *affordances*, as outlined by Gibson and those that followed him. A platform's affordances describe the use of that platform as a function of the user's perceptions of what one can do with that platform. Gibson (2014) uses the example of a rock and how different species of animals view that rock differently: as a tool, as a way to hide, as a way to warm oneself. Each use is predicated on a different set of functions that the rock can fulfill given its physical characteristics (or features). A monkey may use it to crack open a hard-shelled fruit while a lizard uses the heat retention of the rock as a way of staying warm. The point is that these uses are individual to what we might call the "user" of the rock. The rock is not just a rock—but a set of potential actions that one could use the rock for. I could kick it, throw it, use it as a tool, and so on. An affordance is not just something that an object does, but something that users perceive the object being used for.

Moving beyond a rock and into more complex mechanisms, uses of modern-day communication platforms are also governed by their affordances. An affordance is not a feature of a platform (such the ability to tag other users in an online post) but is the perceptions of the use of that feature (Evans et al., 2017). While features are important, it is not enough to say that Twitter has a character limit so therefore the content on Twitter is unique only because of the 280-character constraint; that is an obvious point. It is the interaction of the user and the feature that creates the affordance. In the case of tagging users, the affordance of the platform could be called network connectivity, which is made possible by the tagging feature. Similarly, a feature of television is the wide spectrum of audiences that could see the broadcast. Consequently, a user could create a message that is broadcast to a large number of people, by using the television affordance of mass communication.

This project evaluates platforms of political campaign communication by looking at both their technical features and their user affordances. It hopes to address a shortfall in political communication by identifying the relevant combination of technical features and user affordances that define communication across platforms. Further, it evaluates how they influence campaigns and political communication. There is a broader point here, as well. This project is about how platforms are inclined towards certain content and, importantly, is predicated not on the specific platforms that are available at the time of this writing, but on how different structures of platforms shape content. The dissertation engages with the 2016 election, but the arguments are meant to extend beyond that narrow scope and define a more comprehensive way of evaluating campaign content. The following subsections outline both technical features and user affordances.

Technical Features

As has been perhaps over-noted, Twitter has a character constraint—previously 140 and now 280—which inherently limits the amount of content that can be transmitted. Newspapers limit the space available for advertising, as even a full-page ad can only be as large as the newspaper page itself. These are descriptions of the technical features of a platform. Every platform contains a multitude of features, some of which are used extensively, while others, like the "poke" feature on Facebook, hardly at all (Wickman 2017).

Features are useful and important to understanding how political communication plays out on each platform. I do not attempt to consider all of each platforms' features; rather, I reflect on features as they relate to the presence and structure of text, audio, photo, and video content as described by McLuhan, as well as new forms of information, such as social endorsements. By focusing on features that enable or constrain these categories of information, I can distinguish platform uses as the basis for understanding affordances and how they shape political communication. For example, Instagram defaults to a square shape for picture uploads as opposed to a traditional rectangular format. Consequently, a user who posts content to Instagram must navigate this technical structure, either by adjusting how they take the picture originally or by cropping and editing out content as they go to upload. This alters the information that is produced on Instagram by focusing images on specific scenes and forcing users to make choices about what they include and what they do not.

At a basic level, each type of content is constrained by the ability of a platform to communicate it. A debate lacks the structures for a candidate to broadcast their own photos, for example. Newspapers lack any form of video and audio information. Text constraints vary widely but can most easily be categorized as either limiting the text that can be communicated or allowing for "linking text," such as hashtags, mentions, or hyperlinks. Limits on text also include length constraints (Twitter or newspapers page limits). They can force a user to be deliberate about what words they choose to communicate (Baldwin et al., 2013; Treem & Leonardi, 2013).

In contrast, linking text has changed the nature of communication, primarily on digital platforms. Twitter, while it did not invent hash tagging, was instrumental in the spread of hashtags as a known and acceptable form of communication (Chang, 2010). The social convention of using a hashtag has become an integral part of tweeting (Bruns & Burgess, 2011; Blaszka et al., 2012). This is a technical feature that has altered the ways in which individuals communicate through Twitter. Hashtag usage later spread to other platforms, such as Facebook and Instagram. Similarly, the use of hyperlinks drastically expanded the scope of information that was readily available to consumers. Platforms which allow for such linking text inherently have more information than those which do not.

Almost every platform has some form of text constraints, although some are much tighter than others, such as Twitter's hard character count. Looser constraints include debate timing rules, which somewhat limit how much the individual can say, though they frequently go beyond their allotted time. Another component of limiting text is the ability to edit what is said. Most communication platforms allow the candidate to edit and hone what they say before it is transmitted. However, live broadcasts (debates, speeches, "live" video on Facebook, etc.) do not allow for the candidate to have complete control over their message. This opens up the possibility of different types of information being communicated depending on the nature of the "editability" of the statements (Jesnsen & Dyrby, 2013).

The introduction of audio as a form of communication clearly altered the structure of information production and consumption. Audio constraints describe features of a platform that allow for the broadcasting of spoken word. These features often overlap with video constraints (such as television which allows for both simultaneously) but do differ. Audio constraints are about spoken word and music, not visual information. Radio, for example, allows for the same audio transmission as television. Radio, television, and social media platforms can all broadcast just audio, such as the multitude of "open mic" recordings that occur. Mitt Romney's 47% comment, for example, came from a recording at a fundraiser. There is video, but the camera is located on a table and the video does not provide much information as to what is going on. In fact, one can barely see Romney past the heads of the attendees. What is available, however, are the words that Romney said and someone listening to the audio can easily understand the meaning behind what he is saying without having to watch the video.

I also consider audio constraints as the ability to broadcast spoken tone (Schuller et al., 2011). Platforms that allow for audio contain the actual words, which can elicit emotional states (Nabi & Green, 2015), as well as way in which they are said (e.g. Abelson et al., 1982). That being said, there are occasionally limits on audio length as well as content. Snapchat uses limited length transmission, which shortens what can be said on that platform. The length of a TV ad, while not strictly constrained, is limited both by the money involved in airing the ad as well as the attention of the users. Finally, various platforms operate under different legal regulations. A politician can say pretty much anything they want on a social media platform but are more closely governed by platforms that are controlled both by other entities, such as television stations, and federal regulatory agencies.

The ability to transmit photos is an important feature of political campaigning as candidates have long used pictures as means of communicating information about themselves (Hacker, 1995; Muñoz & Towner, 2017). Features of platforms for photos clearly include the ability to post pictures, but also the nature of the uploading process. Does the photo have to be taken and immediately uploaded from an app, such as Snapchat, or is there an editing process, as Facebook or a newspaper allows? Instagram's square photo configuration is another example of how the uploading process matters. A further consideration is the degree to which photos can be edited and paired with text or other photos. Again, Snapchat allows one to immediately place text right on the photo, whereas other platforms require more elaborate mechanisms.

Video is a comparatively new form of campaign communication, though has become widespread across many platforms. Video elicits different evaluations from users than just spoken word (Scherer et al, 2012; Druckman, 2003). The introduction of nonverbal cues changes the nature of the information presented (Sauter et al., 2010). As far as features are concerned, the ability to transmit video as well as the length on content of video are all important to the structure of information. Snapchat originally limited the length of videos to 10 seconds, and currently limits videos at up to six consecutive 10 second clips. This was actually on display in a presidential election context when Rand Paul conducted a Snapchat interview in 2016. Both the questions and his answers were short and lacking detail or evidence due to the feature constraints of the platform.

The final set of features are those introduced through social interaction with content. The most common examples are "social endorsement" tools, such as Facebook's "like" button and Twitter's "retweet." These are signals to users of the platform that the content may be important. Communications, such as a Facebook post, with more social endorsement are more likely to be given attention (Messing & Westwood, 2012). However, there are other ways in which social interactions matter for platforms. Public opinion dial polls are often used during political debates or State of the Unions. These are real-time approval numbers of a focus group who is watching the event as it happens are presented alongside the live broadcast. They give viewers an up-to-the minute view on how other people who might have similar political identification feel about what is being said. This combination of video broadcasting features and social interaction features add additional layers of information (Kirk & Schill, 2014).

Features are certainly important to shaping information available on platforms. The presence of text, audio, photo, video, as well as social interactions are all predicated on the technical features built into each platform. These features determine the presence and type of content that are available for users. However, features themselves are not solely responsible for what information shows up on a platform. The crucial determining factor is that information produced by candidates on each platform is a function of the interplay between features and the user; the affordances of the platform.

User Affordances

Affordances are the perceptions of what is possible on a specific communication platform given its technical features. A platform is made up of the technical features and user affordances, which shape the information that candidates communicate and how users interact with that information. This section walks through the various ways that affordances have been considered in scholarship.

Some of the earliest work on affordances focused on what scholars might now call legacy platforms (newspapers, television, radio, magazines) and typically did not actually use the term affordances. Consider Stone and Wetherington’s work, which highlights the nature of information consumption on newspapers as being partially habitual (1979). This is driven by the scheduled nature of newspaper delivery as well as habits developed in adolescence. Work by Herzog found a similar relationship for radio listeners (1941). These pieces, and others, highlight how the technical structures and the perceptions of the users interact to form the basis for usage. The relationship between production and consumption patterns cannot be overstated for legacy platforms and this interaction fundamentally shaped the affordances. If the news is on at certain times of the day, then a user can structure their actions such that they are present when the news is available.

While television originally operated under similar structures, the introduction of cable drastically shifted the ways in which individuals consumed information (Lee, 2013). News could be viewed at any point of the day and entertainment television shows were on at all hours. The technical features of the television had changed, breaking up the habitual watching patterns and introducing new modes of access. This allows individuals to tune in when they want to, but also to pay attention to major events at their own pace and leisure (Tewksbury, 2006). This is important as it changed the way individuals viewed news on television as well as their viewing patterns.

Consumption is also dictated by the experience of the platform itself. McLuhan characterized different platforms as being “hot” or “cold” depending on how much of one’s senses were engaged during usage (McLuhan, 1994). Television, which transmits intense audio-visual stimuli, is a “hot” platform whereas a print advertisement is a “cold” platform which does not overwhelm a person with information. McLuhan claimed that “hot” platforms allow for less participation from the recipient. This connects with work on dual-screening, or the act of using one platform while simultaneously consuming another (Vaccari et al., 2015). For example, television does not require as much attention as other platforms do and a user may perceive using another platform at the same time as being desirable. This is especially true in a never-ending news cycle environment where information is repeated often and spending time on Twitter (for example) does not necessarily mean that a user will miss information.

Affordance research has had a revitalization of late with work on internet-based platforms, such as websites and social media (Halpern & Gibbs, 2013). Work on Facebook and YouTube has found that users with anonymity on YouTube were less civil than those on Facebook who generally had their real name and picture for all to see (ibid). Moreover, those on Facebook used lengthier messages to convey their information, perhaps due to the more deliberative perception of that platform. Another explanation is that an individual generally knows their Facebook connections. The platform is built around connecting individuals with one another and their interests, thus making the visibility of one's comments an important consideration before one posts (Treem & Leonardi, 2013).

Twitter may best be characterized as an information distribution platform. The technical structures enable users to quickly share information to a wide-ranging audience. The most obvious example of this is the use of Twitter during the Arab Spring (Bruns et al., 2013). Users of the platform viewed Twitter as a way to quickly communicate information to a large-scale conversation. Because users can share information with both their direct connections as well as other users who happen across their posts, Twitter allows for users to make their information visible to a wide audience. The *visibility* of information is vital to social media's role as a disseminator of information and Twitter especially (Ellison & Vitak, 2015; Treem & Leonardi, 2013).

Snapchat, one of the more recent introductions into the communication marketplace allows a user to share short length clips of video or photo uploads with individuals. The structure of the platform is designed to limit the visibility (clips are only shared with those you select) and the durability (they disappear after a short time) of content. Consequently, the platform is viewed as a way to ephemerally connect with trusted individuals (Bayer et al., 2015). The information is viewed as not necessarily important, but a way to see into someone's daily activities; to get a snapshot of their life. The app and the phone became ways to stay connected to friends and family in a more intimate and casual way than formal messaging services.

However, affordances are not clearly set or agreed upon by researchers. This has allowed for flexibility in understanding how individuals interact with technology, but also has limited cross-platform analysis that is necessary for understanding how a political campaign operates across the vast number of available avenues for communication. To that end, an important point in the discussion above is that affordances are not static. For example, there is no universally agreed upon set of television affordances, or debate affordances. Instead, they are developed from the understanding and goals of researchers. This is advantageous as it allows for diverse studies, but also makes it potentially harder for scholars to coordinate research across projects. Yet there are reasons to suspect that we can make more general claims about affordances than platform specific ones. This is primarily driven by the social nature of affordances. By that I mean, as affordances are a function of technical features and user perceptions, part of those perceptions are driven by what others use the platform for, or what we could think of as perceptions of an aggregated level usage (O'Riordan et al., 2012). That suggests that broader claims about affordances are appropriate because users can consider how their communication goals may be best met across the wide range of platforms they may use. By that I mean, a broader understanding of the media ecosystem allows researchers to consider which platforms are best suited for specific types of content.

New platforms may also be seen as being more open to experimentation with messages. This is interesting in two ways. The first is that it suggests that once a platform had gained some inertia of agreed upon usage there is little reason to change it, or at least change involves a great deal of effort. The second is that the expansion of available platforms means that individuals work to find the appropriate place for their messages, which may occur at the expense of other platforms as the individual integrates a new platform into their perceptions of the media environment.

A Further Note on the Hybrid Media System

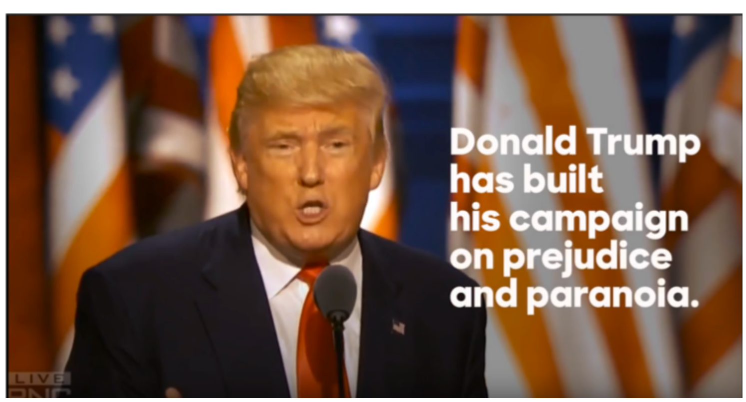
This work is, in part, a response to work on the "hybrid media system" (Chadwick, 2017). The hybrid media system posits that media systems are so intertwined that the content on one, Twitter for example, will resemble the content on any other platform. I have a rather different perspective. Platforms, as outlined here, are a function of their technical features and user affordances. These structure the nature of content on communication platforms. Because platforms are comprised of inherently different features and affordances, there will be systematic variations in content across platforms. I address this more thoroughly at the end of the project, with the hope that the results I present lend greater weight to my argument. However, I deem it necessary to have addressed the relationship between my project and this line of research at the onset. The next section outlines the Platform Audience and Channel Theory as it related to political campaigning.

Chapter 3 Platform Audience and Channel Theory

I want to start my explanation of the Platform Audience and Channel Theory by considering the following examples from Hillary Clinton's general election campaign in 2016 (Figures 3-1 and 3-2). The first is a tweet in which she uses language of inclusivity and a desire to represent the country and not just her supporters. This is a message of unity and positivity. The second figure is a screen grab from a television advertisement her campaign aired. This is a stereotypical negative ad in which she attacks Donald Trump for running a campaign built on prejudice. A fair critique or not, her television advertisement is fundamentally different in tone and content than her tweet is, yet they are produced by the same campaign and same candidate.

Figure 3-1: Clinton Campaign Tweet

Figure 3-2: Clinton Campaign Television Ad



These are illustrative examples, to be sure, but provoke an important consideration. If Twitter is *mostly* comprised of positive and unifying content and television advertising is *mostly* made up of negative attacks ads, then individuals are being exposed to systematically different content. It is not hard to imagine, then, a country in which voters have vastly different ideas about what an election looks like and what the issues of the campaign are depending on where they get their information. If that is the case, then it is not a stretch to envision those same individuals operating with different knowledge and subject to different behavioral implications, such as voting and candidate evaluations. I come to this conclusion because we know that exposure to content that is negative or content that gives policy cues has effects on political outcomes.

Thus far I have outlined why platforms differ. These differences have real-world implications; for instance, they change the calculations and decisions that are made by campaigns. We know from Kreiss and colleagues that campaigns view platforms as serving different ends (2017). That is to say, the perceive the purpose and uses of communication platforms as being different. Campaigns are also strategic in how they communicate with the electorate (Burton et al., 2015; Stromer-Galley, 2019). Indeed, there is a long-standing field of study on how campaigns communicate with intentionality (see Denton et al., 2019 for a review). If it is the case that platforms are a combination of technical features and user affordances, and that those differ by platform, then there are reasons to suspect that a political campaign will use these platforms differently by tailoring their messages to the platform they are using. Further, political campaigns ought to consider how the features and affordances of each platform shapes how the campaign uses them. Yet as of now there has not been a unifying theory as to how the information that political campaigns generate differs across the media environment (which includes new, internet-based platforms as well as legacy outlets such as television and speeches). I set out to do so here by developing the Platform Audience and Channel Theory. In so doing, I hope to set out a theory that offers insights into how campaigns communicate currently, is robust to explain variations in content from previous campaigns and is durable enough to have explanatory power for future campaigns and as-of-yet undeveloped platforms.

Drawing on the research mentioned above, alongside past theorizing about both technical features and platform affordances, I argue that there are two relevant platform dimensions to consider: (1) audiences, and (2) channels. **Audiences** range from ***narrow*** to ***broad***. A *narrow* audience is homogeneous in its partisan makeup. For example, while giving a speech at a rally, the candidate can be relatively certain that the majority of attendees are their supporters. *Broad* audiences, in contrast, are ones for which the campaign cannot be sure of participants' identities or political preferences. There are certainly other ways we could construe a *narrow* or *broad* audience, such as age, racial demographics, income. However, for the purposes of political messaging, political partisanship is the key determining factor I focus on.

The most obvious example of a *broad* audience platform is television advertising. This is because television ads are aired over a large geographic area that will generally include diverse audiences. While a campaign can choose the television station and broadcast time for an ad, hoping to reach a somewhat narrower audience, they do not have near the same certainty of who they are communicating with as they typically do in a partisan rally. Similarly, debates (aired on television) are a *broad* audience platform. Even at the primary stage, audiences watching a debate support a diverse candidate set. Politicians must be mindful of those differences. Comments, attacks, and boasts that might work to core supporters may backfire in the face of voters who are undecided or support another candidate.

Conversely, *narrow* audience platforms would include speeches, Twitter, Facebook, and Instagram. Speeches are a platform where there is a reasonable amount of certainty for the candidate about the makeup of the audience. There are, naturally, exceptions to that rule, such as the Al Smith Dinner in New York for a pro-abortion Democrat, but for the most part it is the case that makeup of audiences of speeches are known to the candidates. Similarly, I argue that social media platforms, such as Facebook and Twitter, are also *narrow* audience. While social media spaces have wide and diverse userbases, regularly being exposed to the content of a specific candidate requires a deliberate act by the user, generally "following" that candidate.

Of course, central to the audience component of platforms is that the candidate must be *aware* of the audience's configuration. In order to actually match content to the audience, candidates must know who is receiving each message. Without that knowledge, then campaigns must be more careful with the types of messages they communicate. Aided by the increased professionalization of campaign staff and practice (Strömbäck, 2007), campaigns put a great deal of time and energy into understanding audiences and demographics (Baldwin-Philippi, 2015).

The other major consideration for platforms is the degree to which candidates must share the attention of the audience. When a platform is shared, candidates are forced not only to get their message out but anticipate and respond to what other candidates are saying. Consider a debate, where what one candidate says can be directly responded to by their opponents whereas a mailer allows a candidate to deliver their message without simultaneously sharing the platform with their opponent. This is also the case with social media, as candidates are open to direct response and engagement from opponents. I refer to this as the **channel** of the platform, ranging from ***independent*** to ***shared***.

Independent channels are ones that are relatively free of interactions with other candidates; especially interactions that can happen close to real time, as it does in a debate. Speeches are a useful example, again, as they are almost always done without the presence of other candidates. Television, given the descriptions above, is an *independent* channel platform. While candidates can certainly air advertisements that critique or call out their opponents, the ability to do so quickly is limited by the technical constraints of television. Designing, filming, and airing an ad all take time. Similarly, speeches are *independent* in that a speech at a campaign event involves no opponents who can respond to things that are said or offer criticisms.

Shared platforms are ones were candidates are able to quickly and directly engage with what their opponents say. An obvious example is a debate where Candidate A answers a question and Candidate B is able to immediately respond to that answer. When a candidate is able to hold their opponents publicly accountable for what they say, that changes the nature of the dynamics between candidates. Debates are, of course, a *shared* platform; as are Facebook and Twitter. They are *shared* because a candidate could easily respond to what another candidate said, even directly on their opponents page. It is important here to note that this is not a binary classification. Twitter is likely more shared between candidates than Facebook is. For instance, there are a few examples of how Hillary Clinton would directly engage with Donald Trump during their candidacies on Twitter even going so far as to tell Trump to "delete (his) account", whereas Facebook does not have the same degree of connectedness.

The point is that, in general, platforms fall along clear lines of *independent* versus *shared* channels and *broad* versus *narrow* audiences. I view audience and channel as existing orthogonally to one another and illustrate that relationship in Figure 3-3. Platforms can be placed in this two-dimensional space. For example, a debate is a *shared* channel and *broad* audience:

candidates are speaking to a diverse political spectrum of individuals while simultaneously having to respond to what their opponent is saying. Conversely, some social media sites are a *shared* channel and comparatively *narrow* audience. The audience is not entirely co-partisans, of course – past work suggest that there are counter-partisans and unintentional exposure (Tewksbury et al., 2001), but the bulk of a social-media audience will be co-partisans, due in part to the fact that social media users generally actively choose to see content from the politician (Prior, 2007).

Figure 3-3: Platform Audience and Channel Theory

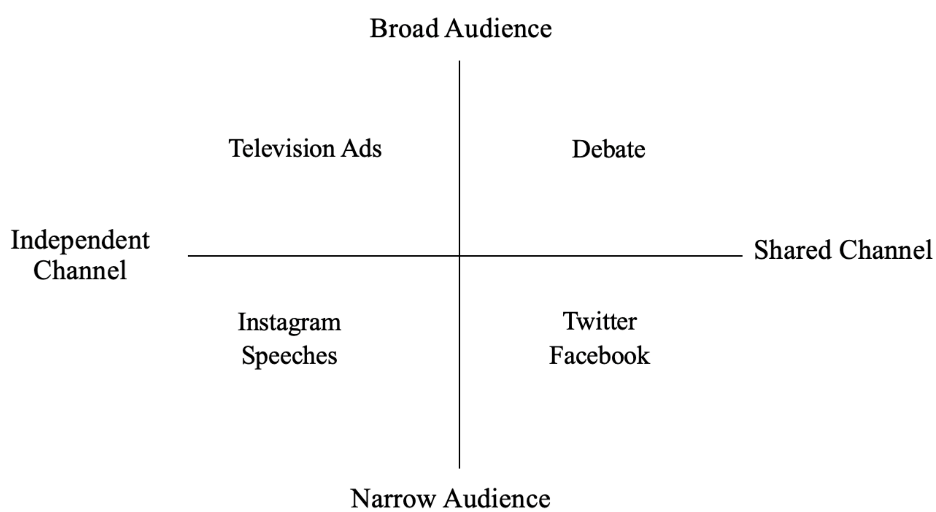


Figure 3-3 is not meant to put forth hard rules about where these platforms lie in relation to one another and the dimensions. Of course, there are ways in which platforms can move across these dimensions, through different combinations of features and affordances. Facebook is depicted in Figure 3-3 as a *shared* channel with a *narrow* audience. This is the case when a campaign posts to their Facebook page; but it needn't be the case for other ways that a campaign could use Facebook, such as paid ads, which can be targeted at people who do not necessarily follow the candidate's account. This would shift Facebook ads to *narrow* audiences and potentially *independent* channel. Similarly, a speech at a national convention is different than at a rally in a non-battleground state with national convention speeches typically given to a broader audience that may include counter-partisans watching on television. Figure 3-3 nevertheless sets out a general framework for thinking about how campaigns view the messages they transmit, given the constraints on those messages, across platforms.

This is the central argument of the Political Audience and Channel Theory. Its aim is to develop a way for scholars to start to think about how a campaign might view the media environment, and how these considerations can influence the content that appears on platforms. It is based on how technical features and user affordances shape the nature of each communication platform. These combine to incline platforms towards different audiences and allows for different channels. As a result, political campaigns view platforms as serving different purposes and being used for different communication goals. In combination, this should lead to platforms having systematically different content on them based on their audience and channel. In the next section, I outline the data that is used for this project.

Chapter 4 Data

In the final days of the 2016 U.S. presidential campaign, from September 1st through November 8th, Hillary Clinton and Donald Trump collectively made 177 campaign stops, rallies, and interviews.[1] In addition to this breakneck pace of events, the campaigns communicated through a wide range of platforms to reach voters. An incomplete list could include: television advertisements, radio advertisements, billboards, yard signs, flyers, mailers, posters, emails, Facebook posts, tweets, Snapchat posts, Instagram uploads, and YouTube videos. The PACT argues that these platforms are all fundamentally different. In this chapter, I am going to lay out the data that I will use throughout the rest of this project.

This project examines campaign communication from the 2016 U.S. presidential election. I chose to focus on a campaign and this particular one for two reasons. The first is that elections are a time of heightened political information production and sharing (Stieglitz & Dang-Xuan, 2013). During a campaign, vast amounts of political information are generated by diverse groups of individuals and organizations and a large number of individuals are paying attention (Tewksbury, 2006). That means there is a great deal of information for an engaged and interested audience during most of the campaign season. We also know that political campaigns matter, not just for the aforementioned determination of electoral outcomes but also in producing the information that citizens take in and integrate into their political preferences (Holbrook, 1996). There is some evidence that this information can change voting intention or behavior through the

[1] https://fivethirtyeight.com/features/the-last-10-weeks-of-2016-campaign-stops-in-one-handy-gif/

introduction of new information about candidates and the country (Huber & Arceneaux, 2007; Holbrook, 1996) and even when a campaign does not introduce new information for voters to consider, there are reasons to think that the content of a political campaign activates the "fundamentals", or short-term economic considerations. (Wlezien & Erikson, 2004; Erikson & Wlezien, 2012).

The second motivation is that it seems especially likely that the content of the 2016 campaign mattered to the outcome of the election. While Hillary Clinton had a slight lead in the polls on Election Day, Donald Trump was within the margin of error. The words that the candidates said and the messages that they attempted to get out to voters may well have had impacts on who eventually won the race. As a result, there is further incentive to looking at 2016 compared to an election where the outcome was more of a foregone conclusion, such as the 1984 Reagan – Mondale contest.

The scope of a presidential campaign's communication is vast, and it is not realistic to acquire all possible communications that a presidential campaign generates. It nevertheless is possible, through innovative capture methods, to gather data from a number of very different platforms, (1) likely a reasonable approximation of what the 2016 U.S. presidential campaign looked like, and (2) a diverse enough set of platforms that there is meaningful variation in both audience and channel. In so doing, I want to find platforms that are relevant to the election, can produce a sufficient amount of data to warrant analysis, and are diverse along the guidelines established above. I selected: live speeches in front of audiences, debates, television advertisements, Facebook, Twitter, and Instagram.

For the 2016 presidential election, 1,745 individuals filed candidacy paperwork with the Federal Election Commission.[2] I do not capture data for all of these but focus on candidates that had a realistic chance of winning a major party's nomination for president. Specifically, I focus on candidates for either the Republican Party or Democratic Party nomination and limit my data to individuals who a) actually declared a candidacy, b) participated in at least one debate, and c) had an active social media presence during their candidacy. For instance, Rick Perry dropped out before any actual primary voting occurred, but was a debate participant and is consequently included. I chose these limits to ensure that I was collecting content from serious campaigns – ones who were actively trying to win the nomination *and* would have communicated enough for me to warrant their inclusion.

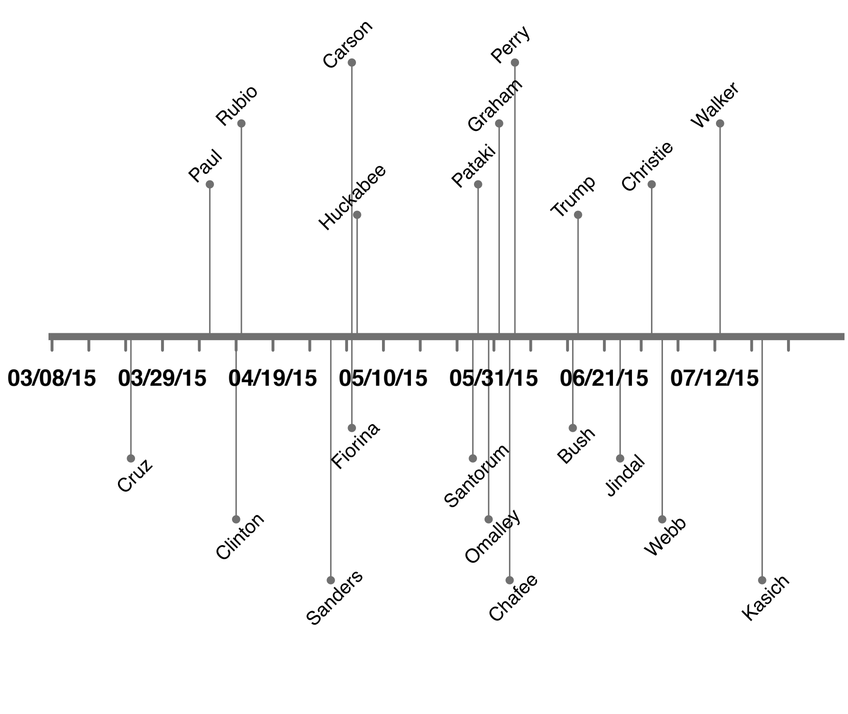
This leaves me with 21 candidates. For the Democrats: Hillary Clinton, Lincoln Chafee, Martin O'Malley, Bernie Sanders, and Jim Webb. The Republican candidates are: Donald Trump, Jeb Bush, Ben Carson, Chris Christie, Ted Cruz, Carly Fiorina, Lindsey Graham, Mike Huckabee, John Kasich, George Pataki, Rand Paul, Rick Perry, Marco Rubio, Rick Santorum, and Scott Walker. In total, the dataset includes 21 candidacy announcement speeches, 23 debate transcripts, 2,579 transcripts of live speeches, 1,441 television advertisements across 205,930 airings, 31,838 Facebook posts, 53,506 Twitter posts, and 4,482 Instagram posts. All told this corpus contains 21,907,373 words. I outline the collection and cleaning approaches for each platform below.

[2] https://www.fec.gov/data/candidates/?election_year=2016&office=P

Speeches

I collected two different types of speeches, though they are combined for the purposes of this project. The first are announcements of candidacy. These are one of the first major public steps that a candidate makes when entering the presidential race and they are a crucial milestone in the overall media narrative that develops around each candidate. Candidacy declarations are scraped from *Time Magazine's* website. A number of websites had the full text of the transcripts available for most of speeches, but *Time* had all of them. The full text of 21 announcement speeches by the candidates totals just over 67,000 words, varying in length from 1,562 to 6,826 words. The speeches were made between March of 2015 (Ted Cruz) until July of 2015 (John Kasich). The text is cross-checked with the actual video of the speech. Figure 4-1 shows the timetable for candidacy declarations.

Figure 4-1: Timeline of Candidacy Declarations



I also collected the transcripts of live campaign speeches, beyond the declaration speech. As outlined above, speeches are an *independent* and *narrow* platform as these are speeches given to an audience that is physically present with the candidate. The speech may or may not be broadcast, but if so, then it is typically only on C-SPAN or a similarly small-audience venue. My presumption, then, is that the candidate is speaking primarily to the audience in front of them, and secondarily, or not necessarily at all, to a television audience. My speech data come from the UCSB American Presidency Project (Woolley & Peters, 2008). There is a total of 276 speeches in the dataset, ranging from 31 to 6,826 words. This part of the corpus is 1,071,364 words in total. The figures that follow illustrate some simple descriptives: the number of speeches by candidates and the speeches by date (Figures 4-2 and 4-3, respectively).

Figure 4-2: Speeches by Candidate

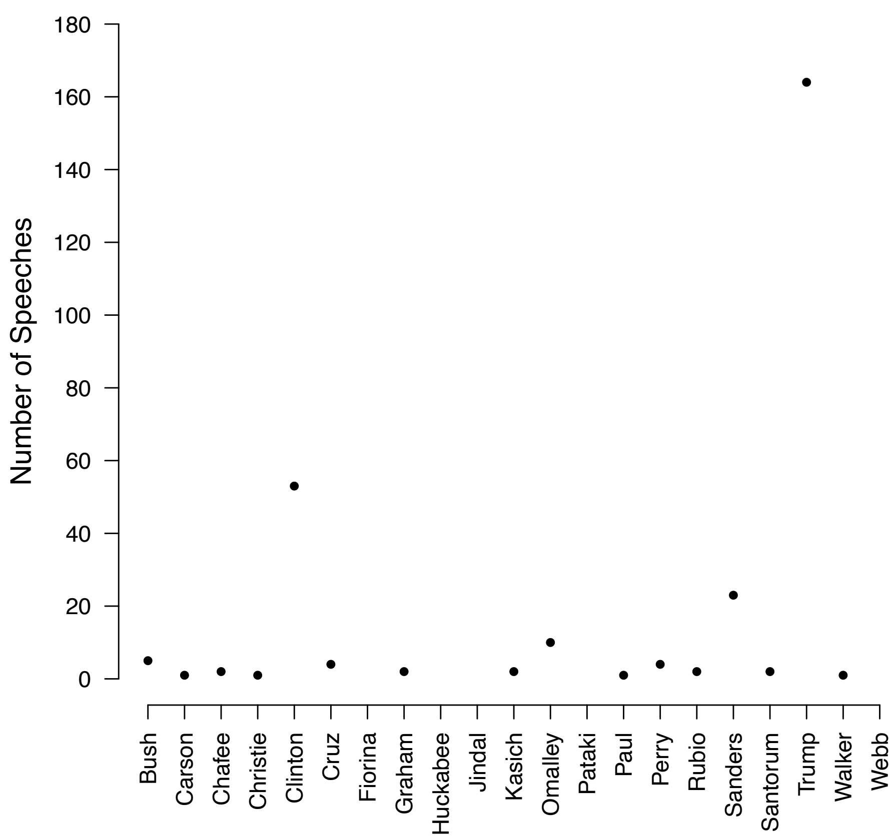
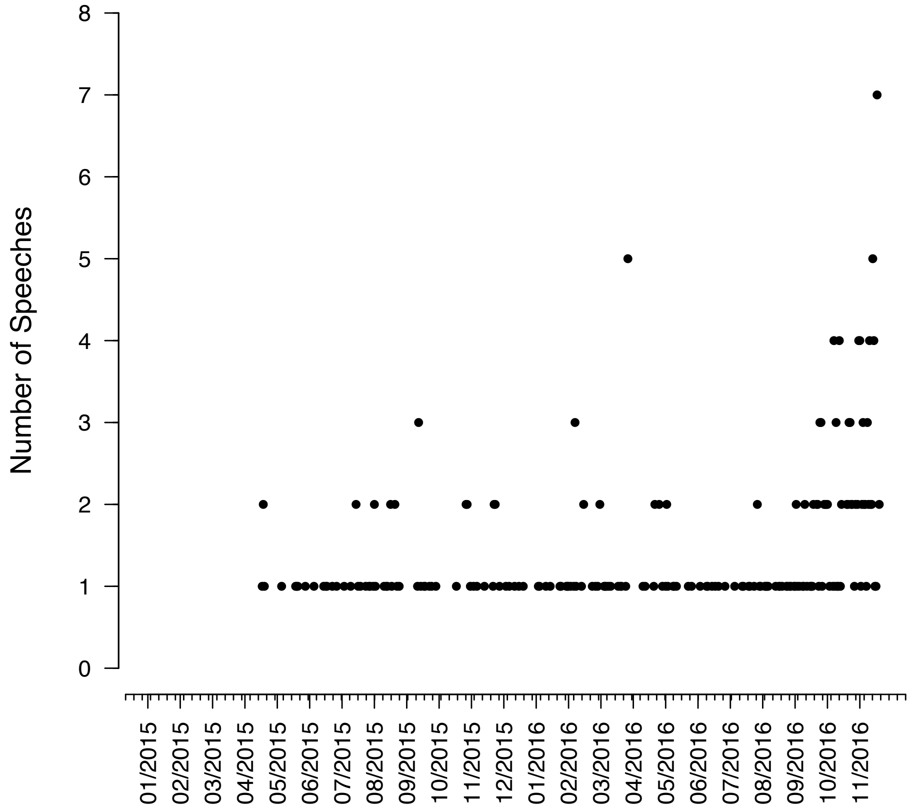


Figure 4-3: Per Day Speeches

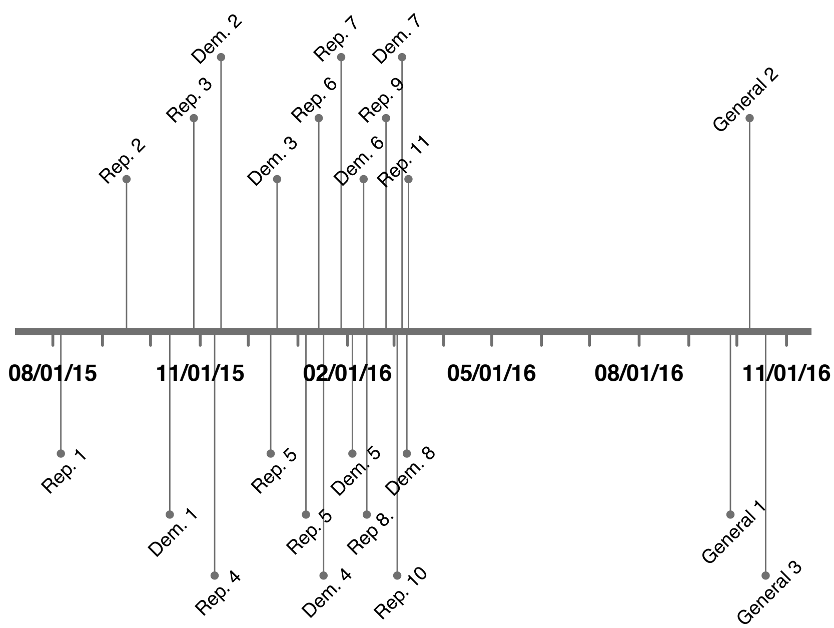


I also look at speeches by paragraph. The rationale behind this is that a speech is much longer in length than any other platform in the dataset, which makes direct comparisons hard as a speech can cover significantly more ground regarding topics. Further, speeches are not generally a single message. Instead, they move across topic and theme. I am inherently losing part of the message that a candidate intends their speech to convey by looking at a speech as one unit. The basic trend is the same for speeches by paragraph as it is for total speeches. The analyses that are in subsequent chapters relies on the paragraph corpus.

Debates

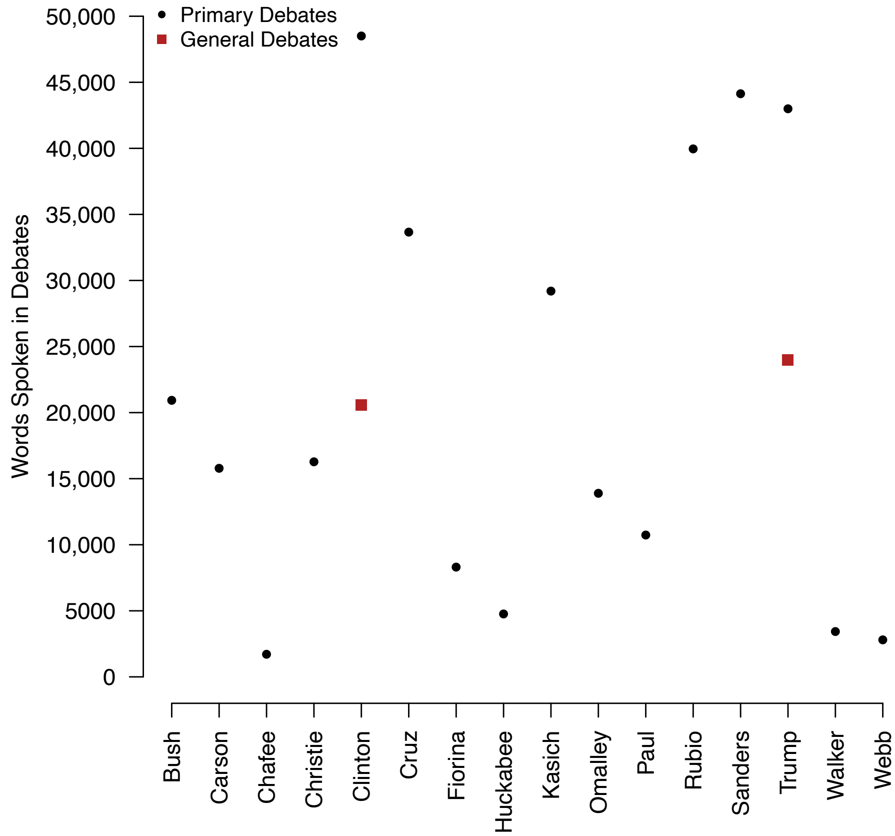
There were a large number of debates throughout the primary and general election, 23 in total with 20 primary debates across both parties and 3 general election debates. Debates are an interesting platform as they are one of the few times that candidates are physically in the same space as one another. They are also nationally broadcast and draw diverse audiences. This means they are a *broad* audience, *shared* channel platform. Figure 4-4 shows the timing for both the primary and general election debates.

Figure 4-4: Timeline of Debates



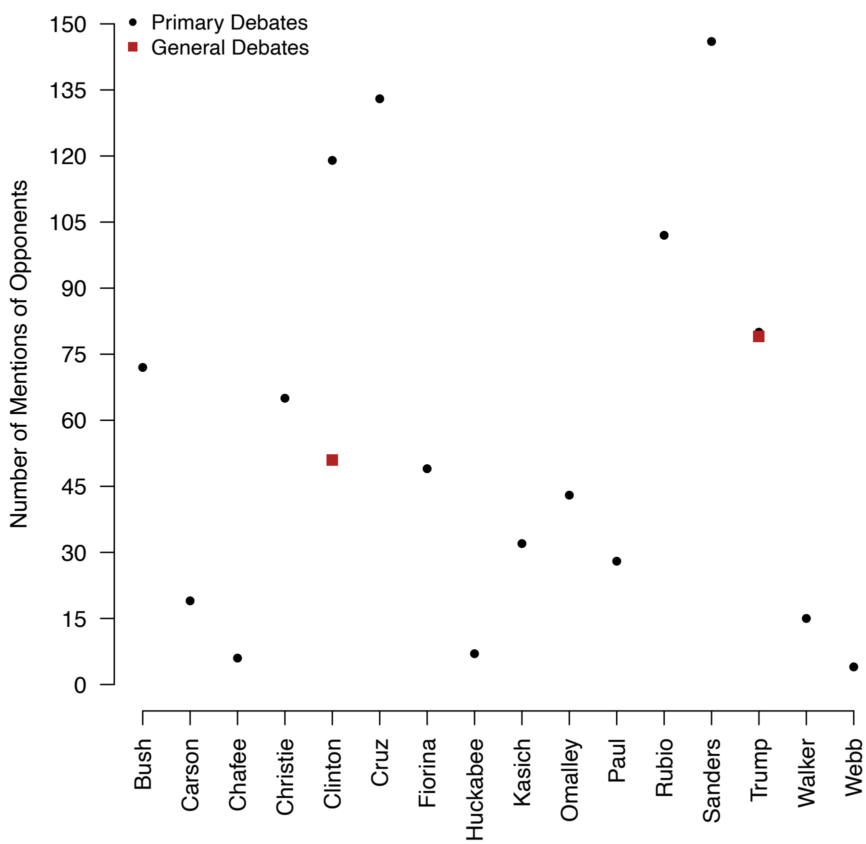
Debate transcripts for each debate were collected from *Time Magazine's* website, just like announcement speeches. The debates are organized by time-order and broken up by speaker, so that each time someone talks is a distinct observation. These range from August 6th of 2015 until April 14th of 2016 for the primaries and September 26th, October 9th, and October 19th for the general election. The debates total 432,176 words.

Figure 4-5: Debate Words Spoken by Candidates



Again, descriptives are provide here. Figure 4-5 shows the amount of talking that each candidate did during the debates. For Clinton and Trump, they have two separate points, the black circle for their primary campaign debates and a red square for their general election debates. Naturally, Clinton and Trump have the most total words (when combining those two data points) as they were involved in the most debates, despite Trump skipping debates during the primary, including the three general election ones. However, we can also see the value of having a smaller field, as was the case with the Democratic primary. Both Clinton and Sanders had more words spoken during the primary debates than any of the Republican candidates did, a testament to each candidate getting more time to talk. I also look at the degree to which a candidate mentions another candidate by name during a debate. This is a crucial component of the *shared* nature of the channel. One argument that I make with the PACT is that candidates are cognizant of their forced interaction with opponents and that changes what they say. By looking at the number of times that candidates mention their opponents, we can see the degree to which this interaction is acknowledged by name. One possibility, however, is that candidates are unwilling to use their opponents' names in a debate as it acknowledges them as a contender. Again, Clinton and Trump have two data points based on their primary (black) and general election (red) debates (Figure 4-6).

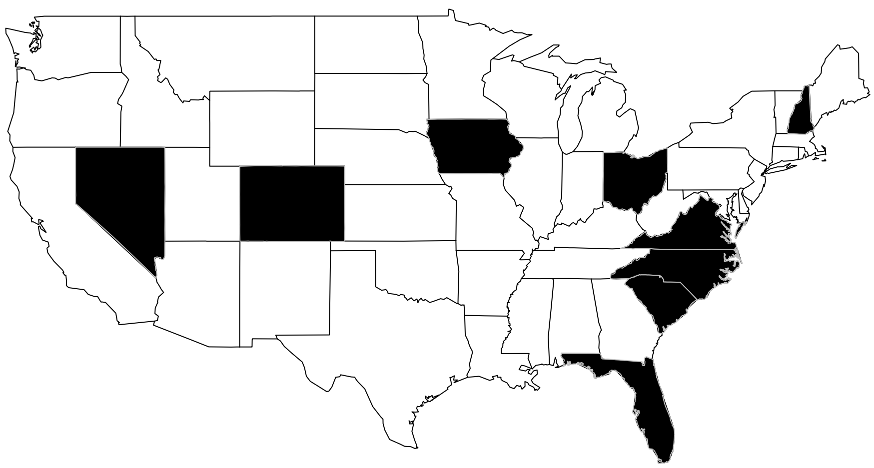
Figure 4-6: Debate Mentions of Opponents by Candidates



Television Advertisements

Television advertising is a long-standing focus of political campaigning research, though may have lost some of its prominence in the era of social media. Television ads are pulled from the Internet Archive and include advertisements that ran from October of 2015 until November of 2016. The Internet Archive is a non-profit digital library that, among many other services, provides an archive of over 400 billion websites through The Wayback Machine. Further, they have a number of other datasets, the most relevant of which to this project is the Political Ad Archive.[3] For 2016, this repository includes 1,446 unique ads aired 205,930 times in specific markets. While not an exhaustive list of every ad aired during 2016, it provides an incredibly useful snapshot of what types of ads were being aired during the campaign. Figures 4-7 and 4-8 show the states for which I have television ads for the primary and general election, respectively.

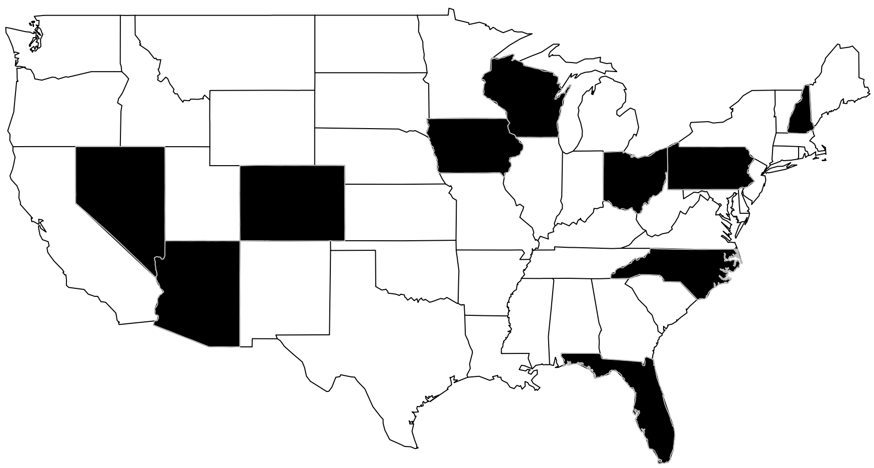
Figure 4-7: Primary Television Advertising States



The primary dataset includes ads aired in Colorado, Florida, Iowa, Nevada, New Hampshire, North Carolina, Ohio, South Carolina, Virginia. The general election dataset has ads from Arizona, Colorado, Florida, Iowa, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, and Wisconsin.

[3] http://politicaladarchive.org/

Figure 4-8: General Election Television Advertising States



In total, there are 162,565 words in the advertisements, ranging from 4 to 660 in any single ad (Figure 4-9). The data also includes statistics on number of runs and where the ad was played. These data include ads aired by both of the major candidates as well as their PACs and other interest groups. All of these are transcribed, but I only use those advertisements paid for directly by the campaign to elect whichever candidate is in question, and only ads that are in English. The ads are listed in the dataset on a per-airing basis; meaning that each time they are aired is a separate case. This essentially weights ads by airings, which I regard as a more accurate measure of the 'signal' that candidates are trying to convey through advertising.

Figure 4-9: Number of Advertisements By Candidate

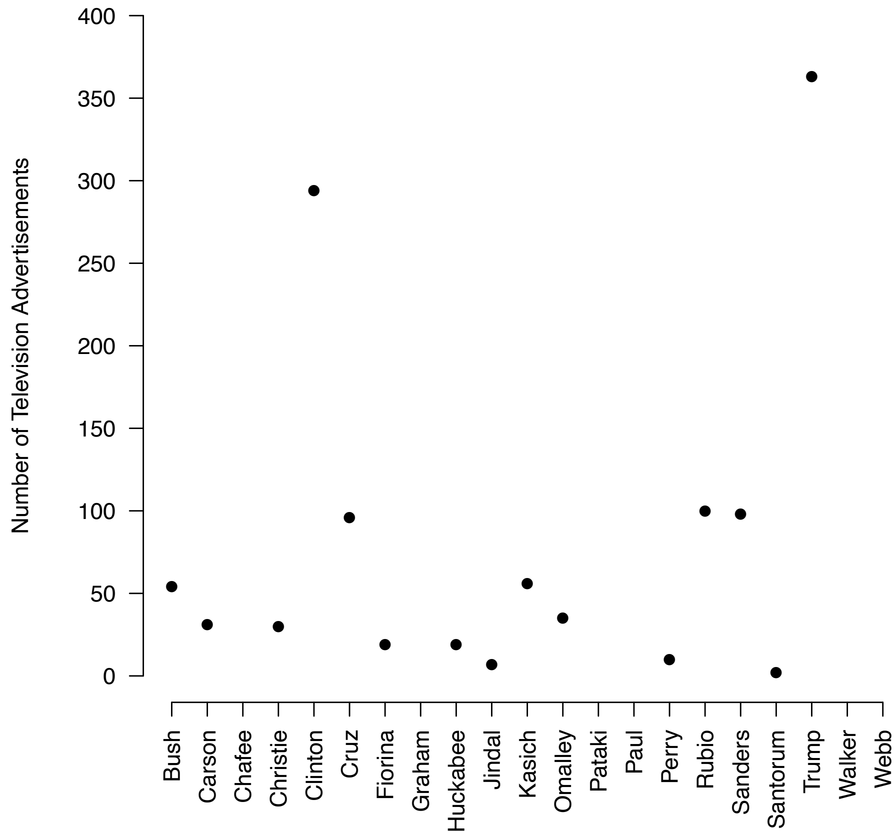


Figure 4-10: Number of Airings By Candidate

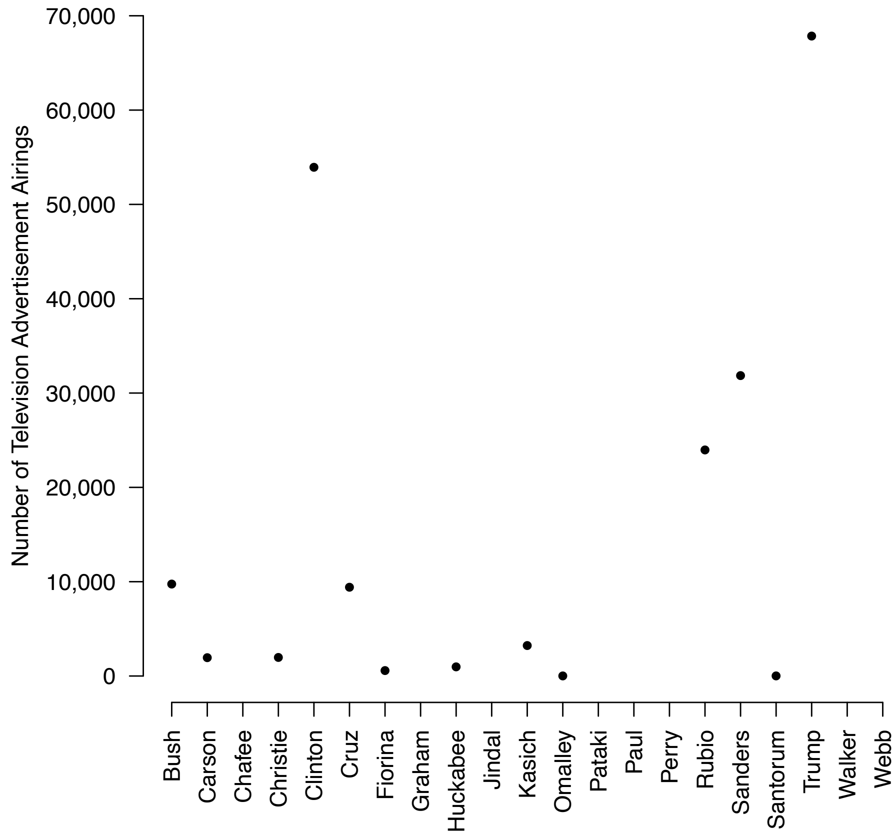
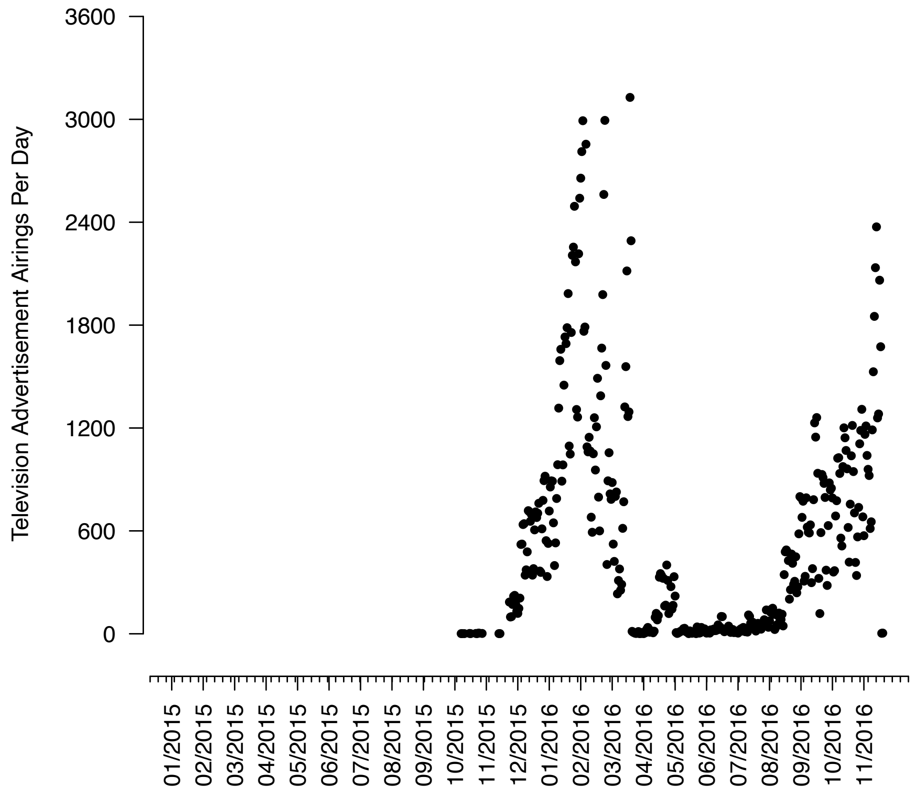


Figure 4-11: Number of Airings Per Day



Social Media

The next three subsections outline social media content. I chose to capture Facebook posts, Twitter, and Instagram. This is not an exhaustive list of social media used in the 2016 campaign, of course, but I focus on these platforms for two reasons, one theoretical and the other practical. The first is that they are among the top social media sites by users (Greenwood et al., 2016). The second is that these platforms have, or had at the time of data-gathering, APIs that provide a researcher with the tools needed to pull the text of posts.

An API essentially allows someone to "call" data from a website. Each of these platforms, and almost all websites, store data in a database and when a user navigates to a page on the site, data is populated from these databases. Thus, the picture you see on a Facebook post is not actually part of the page but is being loaded from where it is saved in a database. By using the API, a researcher is given access to what is functionally a search engine for the database and can access whatever content the page allows them to. By constructing a query to each API, I am able to gain access to the content created by the official campaign pages of each candidate. I describe this process for each platform in detail below. Briefly, I used Python to write scripts for each site that used a list of candidates and iteratively pulled data from that platform.

There is wide divergence in just how useful an API can be for researchers. Some platforms have robust and open APIs, such as Twitter. Facebook, on the other hand, shutdown access to their API, removing the ability for scholars to easily access content. This, in part, has led to an over-reliance on those open platforms that scholars are able to gain access to, such as Twitter, rather than looking at a totality of platforms which do not allow access, such as Facebook. While there is an argument to be made that any data is better than no data, there has been a trend in scholarly fields to a) paint social media with broad strokes based on Twitter data and b) generalize to populations based on Twitter users. Part of what I hope to accomplish with the PACT is to encourage scholars to reject these mindsets and approach platforms, including social media ones, more thoughtfully.

Facebook

Facebook is the largest social media site and one of the top-5 most visited pages on the internet. With over 173 million Americans on Facebook in 2016, having a presence on Facebook is functionally mandatory for campaigns.[4] I classify Facebook as a *narrow* audience, *shared*

[4] https://www.pewresearch.org/fact-tank/2019/05/16/facts-about-americans-and-facebook/

channel platform. This is because posts are generally seen by a candidate's supporters but can also be interacted with by a candidate's opponents as well.

The Python script for Facebook searched each candidate's page for posts. Facebook allowed searches to pull posts back to the beginning of the creation of the individual page. The API allowed access to the full text of each post and any images, videos, or URLs that are included. In addition, it will provide the number of likes (broken down by the type of like), number of comments, and number of shares. The Facebook corpus contains 34,600 posts and 1,335,064 words. Below I show posts by candidate (Figure 4-12) and posts by day (Figure 4-13).

Figure 4-12: Facebook Posts by Candidate

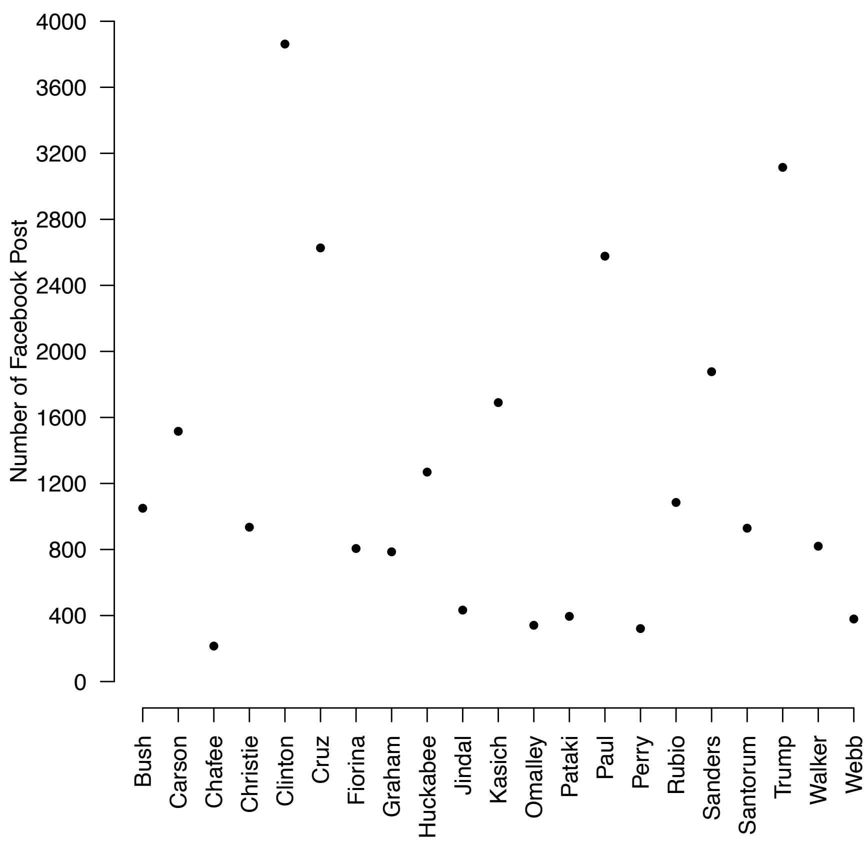
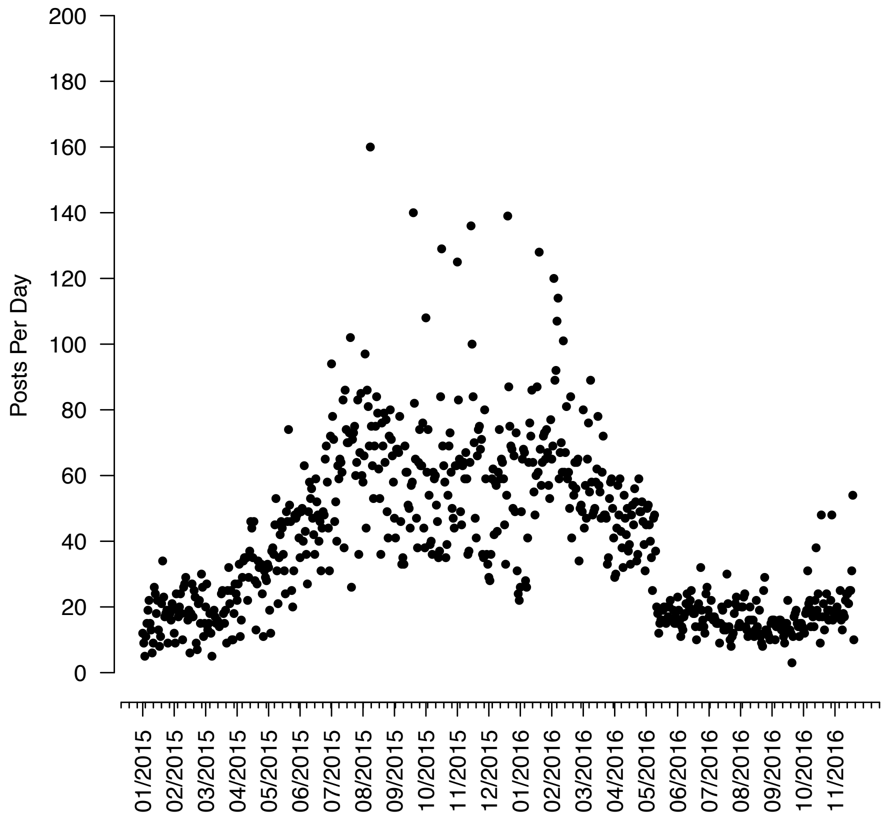


Figure 4-13: Facebook Posts by Date



Twitter

Like Facebook, Twitter is a *narrow* audience, *shared* channel platform. As I mentioned in previous chapters, that is not to say that Twitter and Facebook are equally *narrow* or equally *shared*, but that their features and affordances structure them to be some degree of *narrow* and *shared*. This is an important distinction. Twitter may, in fact, be less *narrow* than Facebook as exposing your message to non-supporters may be easier through Twitter due to easy retweeting and commenting. The Twitter API is currently still active and allows searches to go back as far as the last 3,500 posts. I was able to collect the full text of each post, the number of retweets, number of comments, and number of favorites. In addition, I am able to pull any URLs that are included in the tweet as well as hashtags and whether or not the tweet itself was a retweet. For

Twitter, I have 53,500 tweets across all candidates, totaling 995,433 words. Recall that these are just tweets made by the candidate and not ones made by other individuals discussing the candidates.

Figure 4-14: Twitter Posts by Candidate

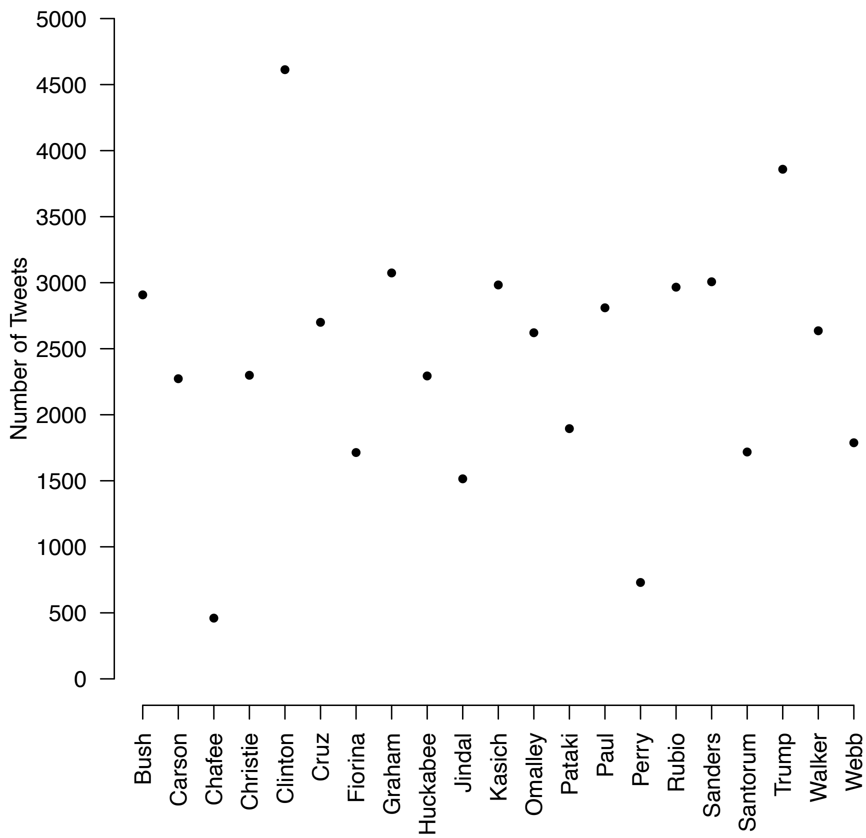
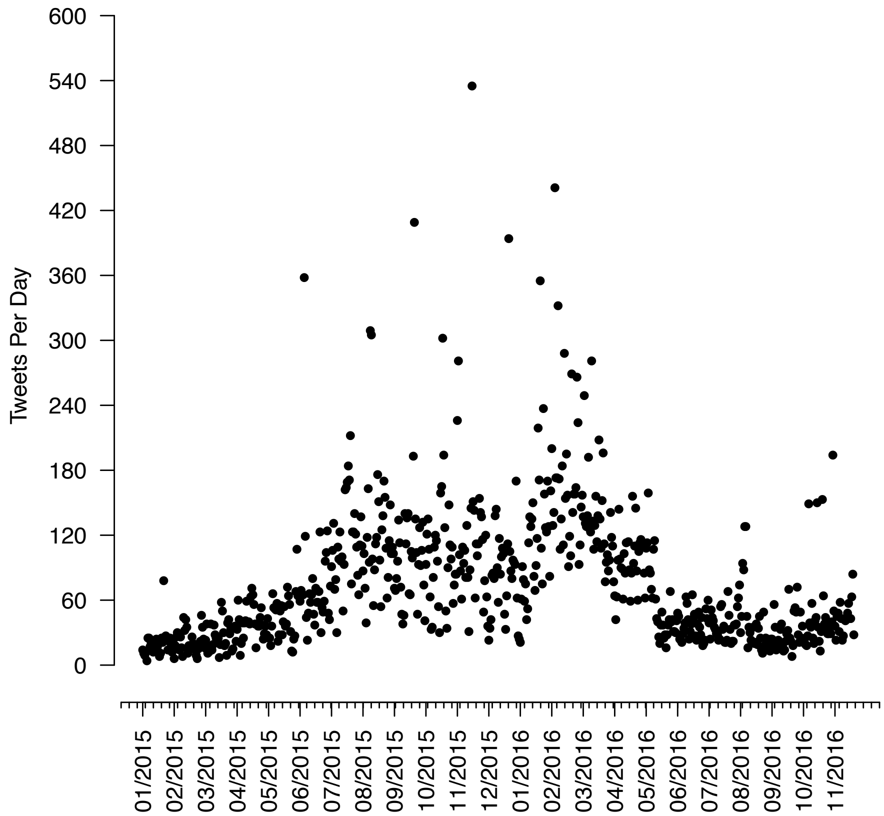


Figure 4-15: Twitter Posts by Date



Instagram

Finally, I collected images and videos posted on Instagram. Instagram is a *narrow* audience, *independent* channel platform. This dataset was collected from a scraper that would iteratively go through a list of candidate account names in a csv file and download their posts. This is different than the API access that Facebook and Twitter offer as Instagram did not have a public facing API at the time of data collection.

In total, there are 4,482 pictures in the Instagram dataset across 14 candidates including: Jeb Bush, Ben Carson, Chris Christie, Hillary Clinton, Ted Cruz, Carly Fiorina, Mike Huckabee, John Kasich, Martin O'Malley, Rand Paul, Rick Perry, Marco Rubio, Bernie Sanders, and Donald Trump. Figures 4-16 and 4-17 show the breakdown of Instagram posts.

Figure 4-16: Instagram Posts by Candidate

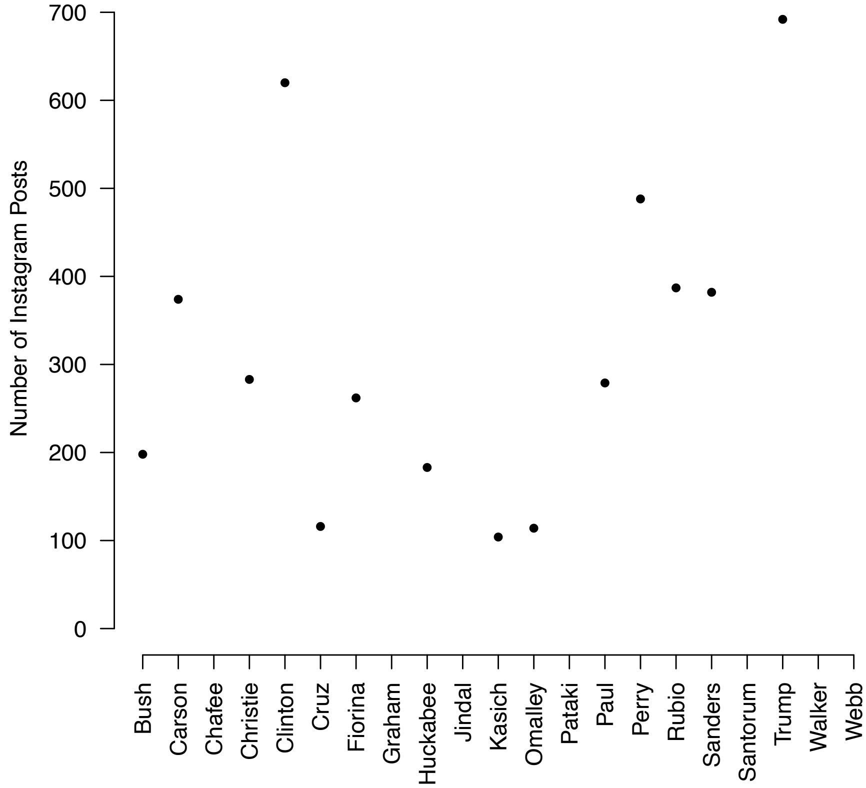
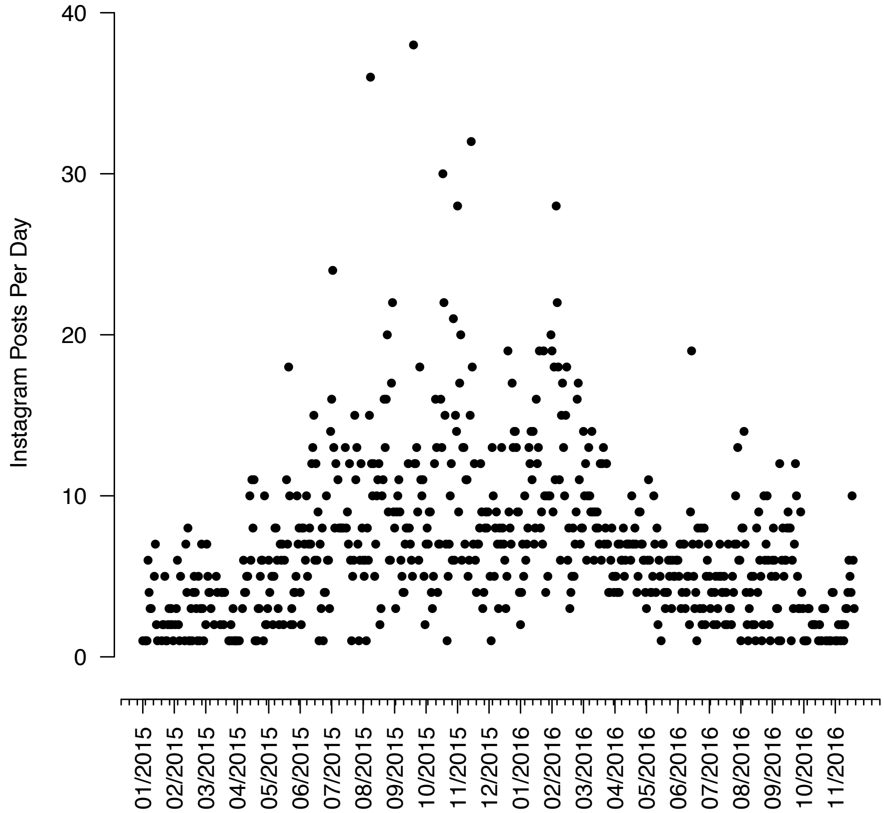


Figure 4-17: Instagram Posts by Date



Dataset

This is a large and complex dataset. The data described above forms the basis for what follows. While this is not an exhaustive dataset of campaign content, it is, to my knowledge, the largest aggregation of campaign communications to date. Further, it represents a wide diversity of platforms with meaningful variations in both audience and channel. This is crucial for the analyses that follow. Figure 4-18 shows the distribution of datapoints by candidate while Figure 4-19 shows the distribution of data points in this corpus. It includes each post, tweet, television ad, debate, and speech from the start of 2015 until Election Day.

Figure 4-18: Datapoints by Candidate for 2016 Campaign

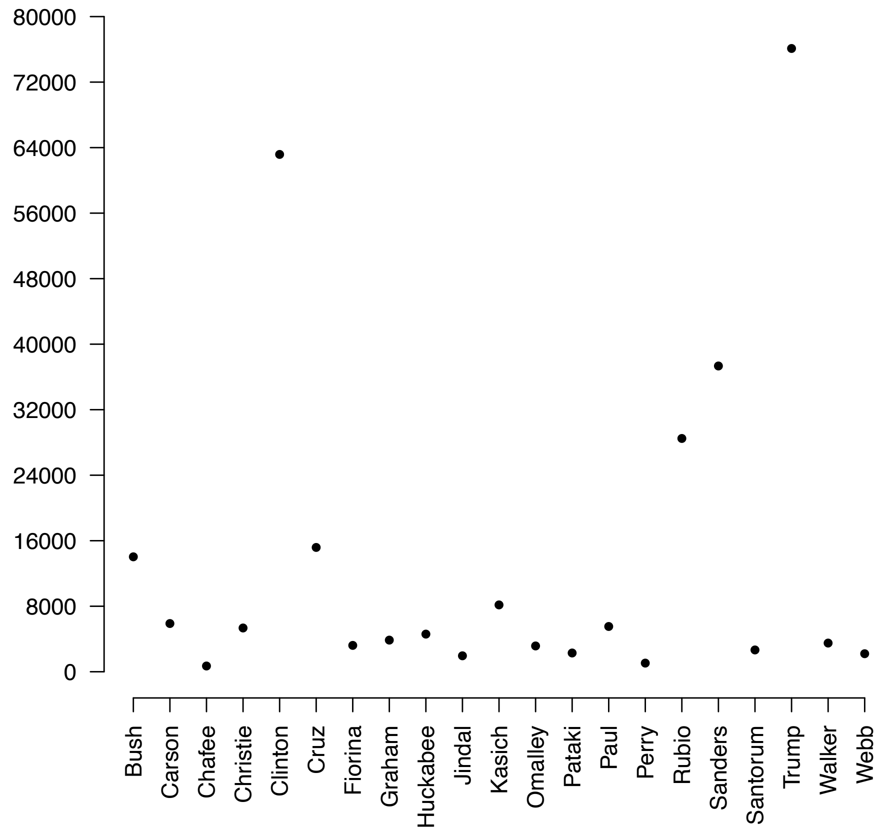
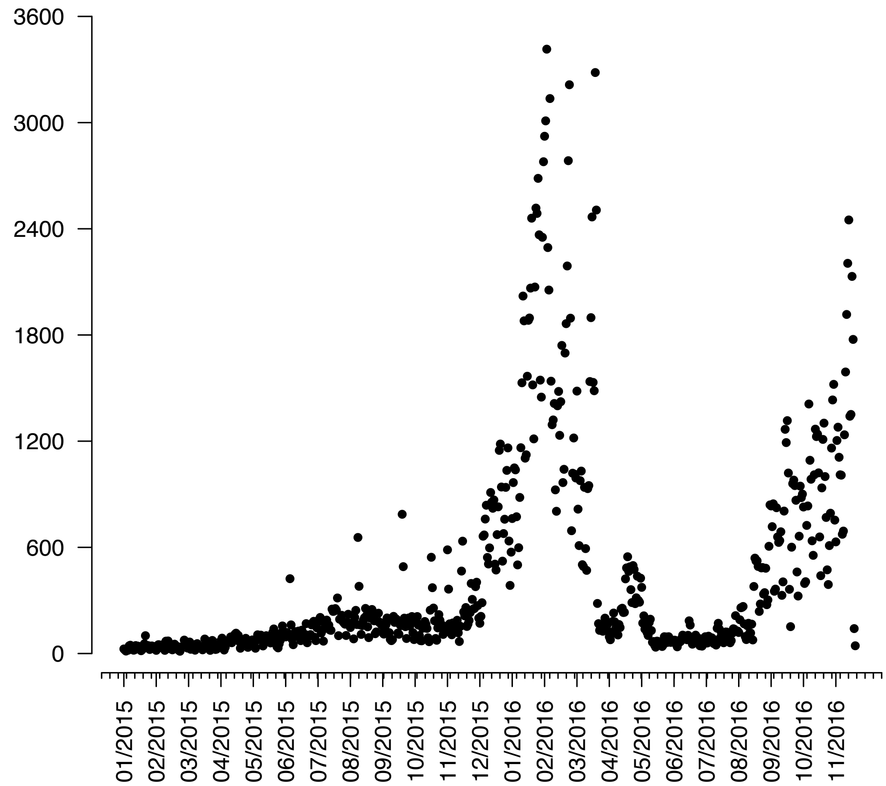


Figure 4-19: Datapoints by Day for 2016 Campaign



What is notable here is that the pattern of communications follows what common wisdom would suggest for a campaign. There are expected spikes at the start of 2016 and during the early primaries, a lull as nominations are locked up, and then further building during the lead up to the actual election. As a final point, I want to examine if the trend that is in Figure 4-19 is reflective of trends in each separate platform. Put differently, does each platform produce a similar over-time trend? This question is not critical to the PACT, but is an interesting descriptive query, nonetheless. It is straightforward to test by looking at the correlations between the number of observations on each platform. I use two different approaches for this. The first is to smooth the social media and television data over a week-long period. The rationale here is that there is so much data with that may be overly clustered or correlated with different days. For instance, there is less posting to social media accounts on weekends than weekdays. Smoothing allows for a more reasonable comparison on these platforms, where I can take rolling seven-day averages of posting behavior which accounts for these differences. However, for debates and speeches, a smoother would be inappropriate as there are not enough observations for a smoother to work. For those, I use a binary specification for debates and simple counts for speeches. Debates are binary as there are multiple observations per debate but only one debate that actual day and speeches are counts as there are sometimes more than one speech per day.

Table 4-1: Correlations Between Platforms by Daily Observations

	Correlation	**P adj.**
Facebook-Debate	**0.196**	**0.000**
Speech-Debate	0.024	0.731
Television-Debate	**0.209**	**0.000**
Twitter-Debate	**0.261**	**0.000**
Speech-Facebook	-0.128	0.073
Television-Facebook	**0.543**	**0.000**
Twitter-Facebook	**0.905**	**0.000**
Television-Speech	**0.236**	**0.006**
Twitter-Speech	-0.012	0.859
Twitter-Television	**0.578**	**0.000**
Instagram-Facebook	**0.804**	**0.000**
Instagram-Twitter	**0.799**	**0.000**
Instagram-Debate	-0.105	0.194
Instagram-Television	**0.635**	**0.000**
Instagram-Speech	0.056	0.813

Table 4-1 shows the correlations between platforms. Facebook and Twitter are highly correlated, at 0.905. Twitter and television ads are at 0.578 whereas Facebook and television advertising are correlated at 0.543. Instagram follows a similar pattern to the other social media platforms. However, correlations between other platforms are lower. Debates and television ads are at 0.209, debates and Twitter at 0.261, debates and Facebook correlate at 0.196, and debates and speeches are at -0.076. Speeches correlate with television ads at 0.236, with Facebook posts at -0.128 and with tweets at -0.012. Lastly, debates and speeches are correlated at 0.024. Speeches are the only platform with non-significant correlations. In fact, speeches are non-significant for all pairings, with the marginal exception of speeches and television, which is correlated at $p < 0.01$ ($p = 0.006$). Altogether, there seems to be a strong connection between social media strategies, with fairly close connections to television advertising. Debates and speeches are, as we might expect, following different patterns of usage.

These data are not inclusive of everything that campaigns produce and is certainly missing content from various candidates and platforms. However, this is still the largest aggregation of campaign content and covers a wide range of platforms that have meaningful differences in audiences and channels. This is, thus, the first dataset that allows for serious comparisons between campaign communications across wide ranges of platforms. At the risk of overstatement, this is a vital contribution to the field already. Aggregation of such a large body of communications across a wide and diverse set of platforms is a, as of yet, lacking resource in the field. What makes this notably important now, is that it allows me to analyze and test hypotheses about how content will systematically vary across platforms and be able to use this large-scale dataset to support my findings. In the next section, I begin my examinations of the content of the 2016 campaign by looking at sentiment.

Chapter 5 Sentiment Across Platforms

This chapter sets out to offer a first set of tests of the Platform Audiences and Channel Theory. To do so, I turn to a well-established literature on positive and negative sentiment in political campaigns and develop some expectations about the ways in which both *independent* versus *shared* channels, and *broad* versus *narrow* audiences, encourage differences in the information conveyed across platforms.

First, I want to turn back to the examples of campaign content from the start of Chapter 3. Recall that I showed two different communications from Hillary Clinton; a positive message on Twitter and a negative attack ad on television. These examples helped motivate this study generally, but they are particularly related to the analyses in the current chapter. There is a long-standing body of work that examines how positive and negative content influences voters. Understanding how this type of content might systematically vary is crucial not only to understanding platform differences, but also to research on tone and political content, behavior, and psychology. In this chapter, I will lay out the theoretical underpinnings of the role of sentiment in political content, explain why it matters to the political process, and lay out and test expectations for sentiment based on the PACT.

Tone or sentiment, which I will use interchangeably, is a complicated concept that has been dealt with extensively across multiple fields (for a brief list of authors, see: Young & Soroka, 2012; Stevens, 2012; Stieglitz & Dang-Xuan, 2013; Cho, 2013). Sentiment, for the purposes of this paper, is part of the psychological process by which individuals experience the world. Sentiment, or affect, is "the experience of feeling emotions" (Crigler & Just, 2012, pg.

212) and is generally thought of as being on a scale of positive to negative. The tone, or sentiment, of a communication is thought to elicit positive or negative affect in the recipients, which can lead to politically relevant outcomes. A tonally negative communication may make individuals experience negative affect, which can have behavioral, cognitive, or evaluative effects. What I am ultimately interested in this chapter are the political implications of negativity and positivity in political communications. By that I mean I am interested in (a) how positivity and negativity are used across platforms and (b) the consequent potential for differential exposure to positivity and negativity. I should be clear that I do not intend to measure things like the actual effect of negativity on voting, or positivity on donations, but instead focus on the tone of political communications by platform. Even so, the impetus for doing so is the vast literature that examines the various ways in which tone has shaped campaigns and political outcomes. I review that literature below.

Why Sentiment Matters

There are a few ways to think about the effects of sentiment in political communication on the public: through physiological, cognitive, or behavioral effects. These are important as they are all deeply connected to political outcomes that we as researchers care about. For instance, messages can activate attention (e.g. Baumeister et al., 2001), change candidate evaluations (Pentony, 1998), or alter voting behavior (Ansolabehere & Iyengar, 1997; Kahn & Kenney, 1999). These are not inconsequential – each has the power to alter elections and the political fabric of the country.

Sentiment matters for political outcomes and negativity may, in particular, have a strong impact on attitudes, behaviors, and cognitions due to the inherent negativity bias that humans have. Negativity bias is the preference for negative information over neutral or positive; such as in news consumption (Soroka et al., 2019) and is rooted in deeply evolutionary processes. We are biologically predisposed to prioritize negative information, for the potential threat that it may indicate, over other kinds of data (Ito et al., 1998). We can extend this thinking into political communications and campaign messages. Citizens are more likely to pay attention to and give weight to negative information over other forms. Indeed, we see evidence of this in research on political campaigning (Cheng & Riffe 2008; Meffert et al., 2006). Systematic variations in negativity by platform means that the content of some platforms may be more likely to draw the attention of users than other, less negative, platforms.

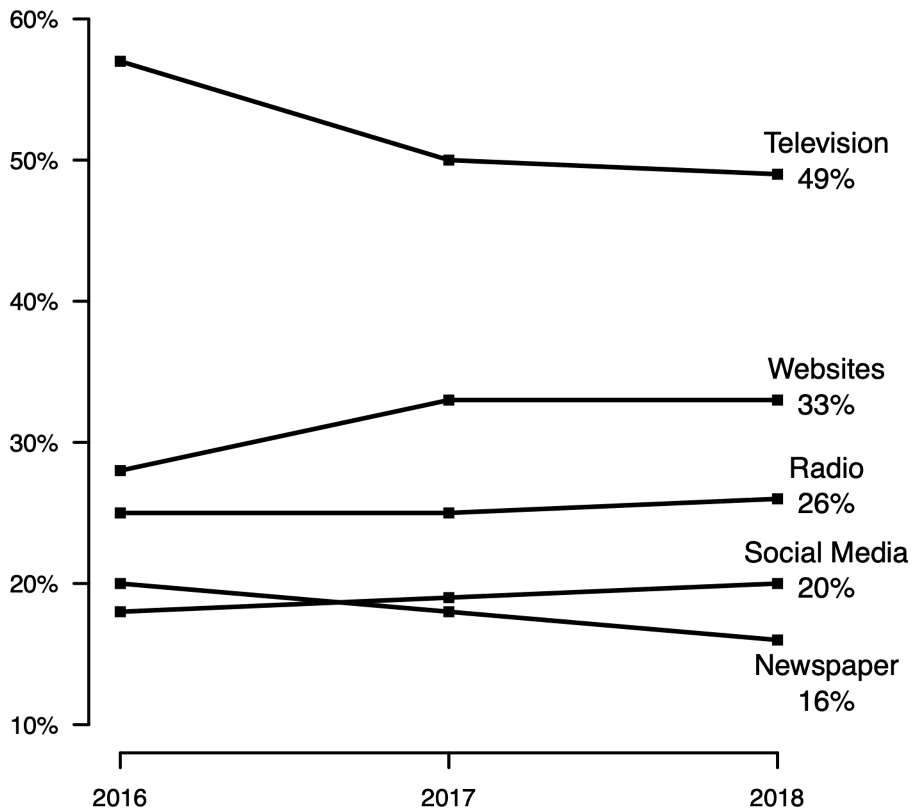
There are also connections between sentiment and cognitive evaluations. Negative information has been linked to evaluations of candidate traits and policy positions (Fridkin & Kenney, 2008). There is evidence that negative campaigning lowers evaluations of the target candidate while simultaneously allowing the attacker to remain unscathed (Pinkleton, 1997), at least as long as the message appears relevant (Fridkin & Kenney, 2004). Moreover, it appears to be very hard to change, or correct, misinformation or untrue views about a candidate once they are ingrained (Thorson, 2016). This means that candidates who can get negative information out early and often may be able to influence evaluations and perceptions of their opponent before the record is able to be set straight. This is especially important to consider when we think about platforms that are *broad* and *independent*, as those are the ones where these types of messages may get the most traction.

We also have evidence of connections between sentiment and behavioral outcomes, notably voting intentions (Ansolabehere & Iyengar 1997, Lau & Sigelman, 2000). For voting, negative ads have been linked to suppressing turnout (Ansolabehere et al., 1994) or increasing turnout (Kahn & Kenney, 1999), and the distinction depends on timing of exposure (Krupnikov, 2014). We also know that using negativity is an approach that candidates and their teams rely on during campaigns. These are often conscious choices as to when and where to go negative (Lau & Pomper, 2004). To that end, I anticipate that campaigns strategically use negativity to drive opponent supporter vote suppression while simultaneously trying to increase the turnout of their supporters.

A great deal of work on political communication is focused on negativity and attack ads. There is, however, evidence that positivity plays a role, most notably in social media communications (Gerodimos & Justinussen, 2015). Here, we see that positivity can be linked to further social media engagement. For political campaigns, user engagement is a highly sought-after metric. Not only does increased user engagement indicate greater attention and focus by users on a candidate's content, but it can also lead to increases in volunteering and donations (Housholder & LaMarre, 2015). Increases in engagement have also been linked to the use of positive and inclusive messages (Stieglitz & Dang-Xuan, 2013). That means that a candidate who wants to encourage engagement and reactions has incentives to be positive in their social media messaging.

All told, there are clear connections between tone and a range of political-behavioral outcomes. What lies at the heart of this chapter, then, is an attempt to discover if there are systematic differences between platforms in their tone. If there are systematic variations, which I outline my expectations for below, then the platforms from which people get their information from could determine their reactions, beliefs, and behaviors. A campaign that is more negative on television than social media is exposing demographically different audiences to different messages. This is the critical motivating foundation of both the PACT and this chapter on sentiment.

Figure 5-1: Percentage of US Adults Who Say They Get Their News Often On Different Platforms[5]



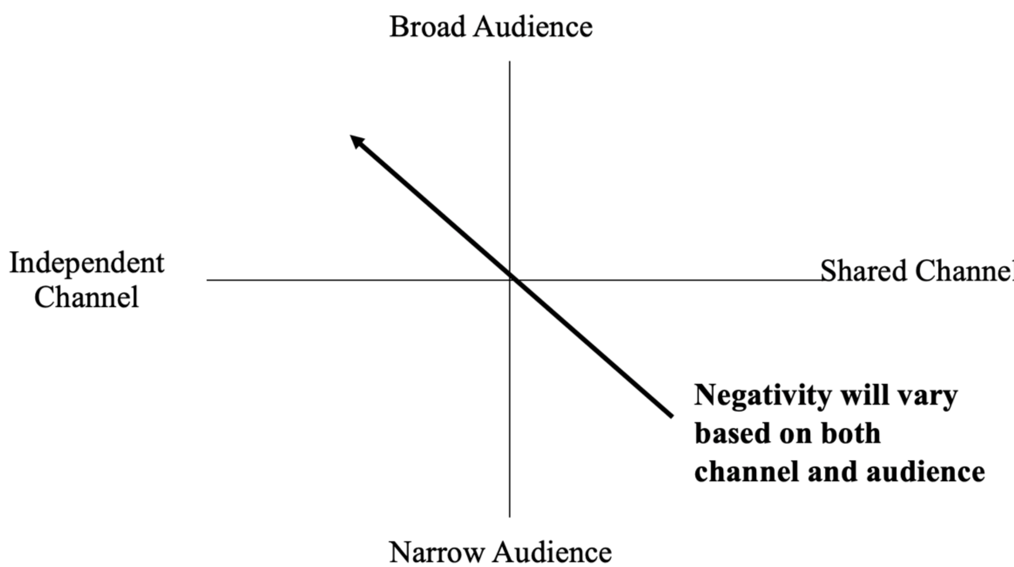
What might that look like? Experiencing a campaign primarily through social media would leave a user with an impression of a generally positive campaign. They may be more likely to engage with communications through features such as liking and retweeting. However, they are also likely to not pay as much attention to content as they would if it was more negative. They also may be less likely to vote or engage in other political behaviors. Compare that person to a voter who primarily experienced a campaign through television advertising. They are likely to see a much more negative campaign, one with frequent attack ads and critiques of opponents. That has the potential to change their perceptions of both their preferred candidate and opponents. This voter may be more likely to vote for their preferred candidate, depending on the

[5] Data from Pew at: https://www.pewresearch.org/fact-tank/2018/12/10/social-media-outpaces-print-newspapers-in-the-u-s-as-a-news-source/

timing of the advertisements, but will almost certainly be paying more attention to the messages that they are exposed to. In these hypotheticals, we are left with two very different voter experiences with tangible changes in their attention and behaviors. This is further compounded by the fact that we know the audiences of platforms differ in important demographic characteristics. Figure 5-1 shows the breakdown of where American adults are getting most of their news and information, suggesting that these hypotheticals may not actually be that farfetched. I argue that this highlights even more the importance of understanding the role that audience and channel play in levels of sentiment across platforms as well as the vital importance that the PACT can play in future work.

Expectations

Figure 5-2: Visualized Sentiment Hypotheses



How might levels of tone vary across platforms, based on a combination of audience and channel? Figure 5-2, above, illustrates the hypotheses that I am testing in this chapter. I propose that negatively will vary based on both channel and audience and will increase (as in tone will become more negative) as we move from *narrow* audience, *shared* channel platforms to *broad* audience, *independent* channel platforms. This means that television will be the most negative and Facebook and Twitter would be the most positive. I outline the reasoning behind these expectations is some detail in the paragraphs that follow.

We have a vast and long-standing body of work on television advertising which generally tell us what to expect with political television ads (Kaid & Holtz-Bacha, 2006). There will often be negativity in their tone and there will also be some substance to them (Geer, 1998; Johnston & Kaid, 2002). What I hope to do here is connect that literature to the PACT and my understanding of the role of audiences and channel. Television advertising is a *broad* audience, *individual* channel platform. With television having such a large reach, it should thus be no surprise that there is a large body of work exploring the frequency and role of sentiment on television (e.g., Kaid and Johnston, 2001; Wattenberg and Brians, 1999; Jackson and Carsey, 2007). For candidates, television allows them to differentiate themselves from their opponents as well as attack other candidates with little fear of quick reprisals.

A television ad can reach a large and diverse group of people. Because they are not talking to only core supporters, identifying their strengths — in contrast to their opponents – is crucial. A candidate does not need to convince their supporters that they are the right person to vote for, after all, just that they should get out and vote. This need for differentiation almost inevitably leads to more negativity, even if the ad itself might not be classified as a traditional attack ad. This is because negative words and affect are inherent to the process of drawing out differences: “Candidate A says this policy is best, but they are wrong. My policy is better.” This connects to Geer’s argument that negative content helps to highlight important distinctions between candidates (2008). Candidates can use negativity to make clear that the other candidate is the wrong choice in the election. When talking to a diverse audience, including supporters, leaners, undecideds, and supporters of their opponents, candidates have a vested interest in drawing out comparisons between themselves and those they are running against.

In addition to using negativity to distinguish themselves, candidates also use negativity to directly attack their opponents. Johnson-Cartee and Copeland refer to this as the direct attack ad hominem advertisements and may be the prototypical example that comes to mind when people think about negative attack ads (2013). What is especially useful about using attack ads on television, is that the platform's channel is *independent*. This means that it is extremely difficult for opponents to respond television through television to critiques and criticisms leveled at them on. The reciprocal nature of this is important. Of course, a politician could very quickly respond to an attack television ad through Facebook, for instance, it requires very little time and no costs. However, the audiences are Facebook and television are different, both in regard to my characterization of audience through the PACT and the actual demographics of audiences. Thus, in order to respond to an attack ad a campaign must develop, produce, and air a television ad, during which audiences are being exposed to the attack ad the entire time. We should expect, then, that negative ads are more present (and subsequently tone is most negative) in platforms where there are *broad* audiences but also *independent* channel.

While television advertising lends itself to negativity because the audiences are *broad*, and it is hard for opponents to respond to attacks quickly, Facebook and Twitter have the opposite characteristics – they are *narrow* audience, *shared* channel platforms. For these, I anticipate more positive content, which may be due in part to the fact that social media promotes a version of self-presentation which focuses on positivity and accomplishments (e.g., Bullingham & Vasconcelos, 2013; Jung et al., 2012; Soroka et al., 2018).

Self-presentation on social media is an incredibly useful concept to understanding how individual users engage with content and curate views of themselves in online spaces (Macafee, 2013; Seidman, 2013). Relevant to this chapter, research has found that users of social media sites try to manage perceptions of their political leanings and the content they share (Marder et al., 2016; Hayes et al., 2015). The idea is that managing how others perceive them is crucial to maintaining the image the user wishes to cultivate. The underlying point here is that content on social media is fundamentally different from what a person actually is, thinks, does, etc. The social media persona is curated and cultivated based on the imagined audience of the user (Marwick & boyd, 2011). There is no reason to suspect that candidates function any differently. The content that they produce on social media sites is curated for the audience they have and the image they wish to present (Kreiss et al., 2017).

We can, again, extend this thinking to political campaigning. There has been some work on how politicians think about their online presence (Colliander et al., 2017; Roper et al., 2004). What those have told us is that politicians are conscious of this tension between audience and content; that platforms with direct engagement and a predominantly supporter-based audience produce a need for a "balancing act" (Colliander et al., 2017) between what the politician views their audience to want and their desire to disseminate their message. In light of that, we should expect there to be more positivity on *narrow* audience, *shared* channel platforms. Audiences are followers who want to see a more personalized version of the candidate.

Political candidates may follow similar strategies and present themselves on Facebook, for instance, in the best possible light. One explanation for this is that they are talking to existing connections. I should clarify here that when I mean social media communications, I am referring to posting directly to one's Facebook or Twitter account, not the other ways in which a candidate could use those platforms to communicate, such as paid advertising. Because followers on social media are predominantly supporters (as in a *narrow* audience), the candidate has a need to tailor their messages and the persona they give off to like-minded individuals. This is likely to incentivize a self-presentation and curation of content towards positive and personal, not necessarily negative and broad. This is also the place of calls to action and requests for donations, volunteering, and social amplification of content; all inherently skewed towards positivity. There is further pressure, as well, which is the degree to which opponents, or their supporters, can quickly engage with attack ads or negative comments pushes candidates into a more positive-driven communication style.

The other major reason to expect more positivity is driven by specific platform features: namely the mechanisms for engagement such as commenting and tagging. Together, they allow for direct interaction between candidates, which means that any negative or attack focused commentary can be immediately, and visibly, responded to by an opponent. In fact, we saw this during the 2016 campaign with interactions between Hillary Clinton and Donald Trump on Twitter, where Clinton used the @ feature to tag Trump in tweets. This is exemplative of an interaction that candidates must be aware of when using *shared* channel platforms, anything they say can be rebutted, refuted, or reconceptualized by their opponents. Thus, positivity is inherently a safer choice for content.

In sum, I expect that:

H1(a): Independent channel platforms with broad audiences (television ads) will be, on average, more negative than other platforms.

H1(b): Shared channel platforms with narrow audiences, (Facebook and Twitter), will be, on average, more positive than other platforms.

What about debates and speeches? I make no specific predictions based on them for one major reason. My argument here is about the interaction between channel and audience and how, when channels are *independent,* and audiences are *broad* we expect negativity while *narrow* and *shared* channels would produce positivity. It is not clear that the heavy lifting is being done by one of those components over the other, so a *broad* audience but *shared* channel is likely somewhere between most negative and most positive, as are *narrow* and *independent* platforms.

Measuring Sentiment

Sentiment is typically measured along a positive-negative dimension (Wilson et al., 2005; Tumasjan et al., 2010; Thelwall & Buckley, 2013; González-Bailón & Paltoglou, 2015). I use dictionary processing to look at the presence of positive and negative sentiment across my corpus. Dictionary processing is a tool that looks for a pre-defined set of words, counts the incidence of each word, and gives a total count for each observation. Below is an example from Jeb Bush during a debate.

> "So, why it was **difficult** for me to do it was based on that. Here is the lesson that we should take from this, which relates to this whole subject, Barack Obama became president, and he **abandoned** Iraq." - *Jeb Bush (August 2015, Republican debate)*

The dictionary looks for the words in this text and finds two negative words, which are in bold: difficult and abandoned. I would then count the total number of words (38) and use this overall score calculation to give me the sentiment for that observation.

*Overall sentiment: ((# positive words - # negative words) / total # words) *100*

In this case, overall sentiment is equal to: ((0 - 2) / 38) *100 = -5.263. This set of calculations is done throughout the entire dataset use a pre-selected dictionary. The choice of dictionaries is important here as the words that are included in a dictionary are vital to the analysis.

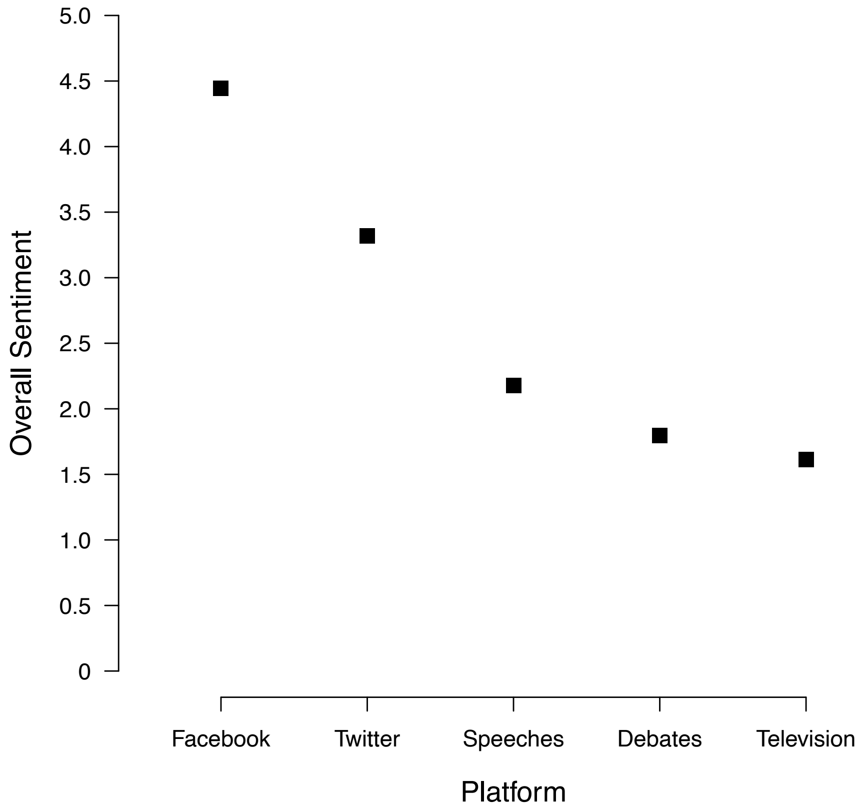
I use the Lexicoder Sentiment Dictionary to code sentiment (Young and Soroka, 2012). The LSD includes 6016 words scored for positive or negative tone, alongside the pre-processing of over 1500 words. The LSD has long been used as a tool for evaluating tone of content (e.g., Young and Soroka, 2012; Murthy, 2015; Soroka et al., 2018). Its value here is that it offers a large, pre-tested dictionary which has been shown to have applicability across platforms, including Twitter (Soroka et al. 2018). I apply the LSD to the entire text corpus, which means the content of all platforms except for Instagram. Mean sentiment across the entire dataset is 2.18 (SD = 8.52), median sentiment is 1.06.

Results

I first look at sentiment across platforms. I do this by looking at the mean sentiment across the entire corpus for each platform in Figure 5-3 below. Mean sentiment captures what a hypothetical voter would see, on average, if they only received content through one platform; this is, in essence, what the "average" experience on that platform would be.

Some results immediately jump off the page. television ads and debates, both *broad* audience platforms, are more negative than other platforms, with television advertising being the most negative. This lines up exactly with H1a, that *broad* audience, *independent* channel platforms would be the most negative. Facebook, in contrast, stands as a clear outlier for positivity, with over twice the proportion of positive words relative to negative words as television, and roughly 40% more positive than Twitter, which itself is more positive that the remaining platforms. Speeches are similar in tone to television advertising and debates, though is more positive.

Figure 5-3: Mean Sentiment Across Platforms



Pairwise Tukey tests (Table 5-1) confirm that each comparison between platforms differs statistically at the $p < 0.001$ level with the exception of television advertising - debates ($p = 0.568$). Speeches and debates differ at the $p < 0.05$ level ($p = 0.024$). Television ads, an *individual* channel with a *broad* audience, exhibit more negativity than other platforms. Debates are also relatively more negative than the *narrow* audience platforms, in line with its *broad* audience status. *Shared* channel, *narrow* audience platforms, such as Facebook and Twitter, are in contrast more positive (especially true for Facebook).

Table 5-1: Pairwise Tukey Tests of Mean LSD Sentiment Across Platform

	Difference	P adj.
Facebook-Debate	**2.646**	**0.000**
Speech-Debate	**-0.378**	**0.024**
Television-Debate	-0.185	0.568

Twitter-Debate	**1.522**	**0.000**
Speech-Facebook	**-2.267**	**0.000**
Television-Facebook	**-2.832**	**0.000**
Twitter-Facebook	**-1.124**	**0.000**
Television-Speech	-0.564	1.000
Twitter-Speech	**1.143**	**0.000**
Twitter-Television	**1.708**	**0.000**

While these findings mostly align with predictions from H1a and H1b; the relationship between debates and television advertising deserves further investigation. Television ads are more negative, although not significantly so. The magnitude of difference is relatively small, as well, at 0.185. However, when we look at the data for sentiment in television ads, we see that Sanders is an outlier at 4.763. While he is not the most positive, relative to the number of advertisements that he aired, he has an outsized influence on the overall sentiment score for television.[6] It is generally not my practice to remove candidates from the dataset, however there is an argument to be made that if one candidate is acting in significantly different ways from others on the platform, then it is appropriate to consider the sentiment scores without them. Without Sanders included in the television scores, overall television sentiment drops to 1.034 and is significantly different from debates at $p < 0.001$. In the interest of balance, I also consider the debate corpus without its most positive candidate who still had a reasonable number of observations. In this case, it is John Kasich. Without Kasich, debate sentiment drops to 1.703, though are still significantly more positive than television ads at $p < 0.001$.

I argue that these findings offer straightforward support for my hypotheses. Results suggest that *broad* and *independent* platforms are more negative than *narrow* and *shared*. I next

[6] Sanders has 31,852 airings in the corpus. While Huckabee and O'Malley are more positively, collectively they only number 984 airings. The total airings for television ads is 205,498.

turn to a few tests of robustness to add further weight to the argument that there are systematic differences in tone across platforms.

Robustness Tests

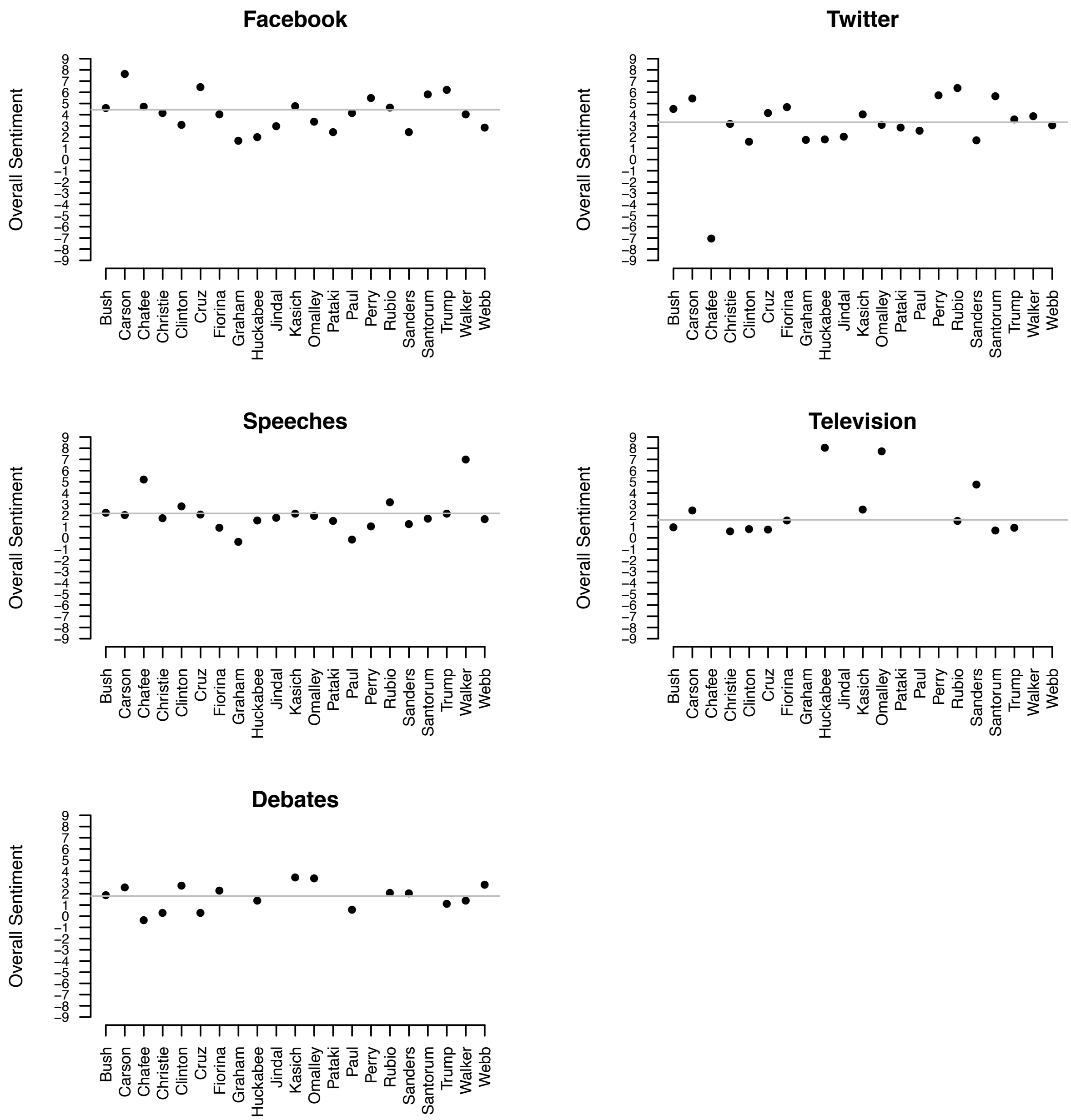
I test the robustness of these findings in several ways. I examine the distribution of sentiment across candidates to confirm that platform differences are not simply the product of different candidates' behavior. I also look at dictionary counts and alternative specifications of sentiment to confirm that my results hold using different measures of sentiment. Most importantly, I look beyond the 2016 presidential election. In each case, results are supportive of my original hypotheses and findings.

Platform vs. Individual-Level Differences

Tone is not uniformly distributed across all candidates. Figure 5-4 below shows the mean sentiment for each candidate by platform.[7] Generally speaking, the candidates hover close to the mean, as indicated by the horizontal gray line. There are notable exceptions, of course. Lincoln Chafee was *notably* more negative than any other candidate on Twitter whereas Martin O'Malley and Mike Huckabee were significantly more positive in their television advertising.

[7] Full Tukey results are in the appendix due to the length of a table comparing 21 different candidates.

Figure 5-4: Sentiment by Candidate and Platform



Given differences by candidates, it is natural to question if the results about systematic biases in platform content that I demonstrate above hold up. I expect that they do – my hypotheses are about the content of platforms, after all, independent of the candidates involved. There are always outliers, and within the realm of political campaigning, candidates are going to operate differently. Yet the *overall* findings align with my hypotheses, which means that in the aggregate, tone is systematically different across platforms in expected ways and that candidates, generally, follow those expectations. We can see this demonstrated by looking at candidates by platform, as I do above in Figure 5-4. However, to further test this, I ran an ANOVA to look at the relationship between candidate and platform. Table 5-2 presents the results of the Type II ANOVA. What we see here is significant variances explained by platform, candidate, and the interaction between the two, with R-squares of 1%, 1.3% and 1.3% respectively. The R-squared of the variance explained by the whole model is 3.4%.

Table 5-2: Platform - Candidate Sentiment ANOVA

Anova Table (Type II tests)	**Sum Sq**	**Df**	**F Value**	**Pr(>F)**
Platform	222621	4	776.889	< 2.2e-16 ***
Candidate	336824	20	235.085	< 2.2e-16 ***
*Platform * Candidate*	366919	67	76.445	< 2.2e-16 ***
Residuals	26188032	365557		

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

What these results tell us is that candidates use tone differently from one another (the candidate variable), there are differences in tone on platform (the platform variable) and that candidates use platforms differently (the interaction term). While all three variables are significant, the important line for this chapter is the platform variable, which tells us that there are systematic differences in tone across platforms. I consider this further confirmation that results are driven, in part, by platform differences. I next look at the words in the corpus.

Sentiment Dictionary Counts

One concern with using dictionaries is that results may be driven by a small number of words. If that is the case here, then there are reasons to question the findings that I do have. In order to check for this, I look at both word densities, or word frequencies and the actual list of most common words. The density of the word counts is shown in Figures 5-5 and 5-6 for the negative and positive dictionaries respectively. In the interest in clarity, I only show words that appear over 1,000 times in the entire corpus. Figures 5-5 and 5-6 show us that many words are used relatively often, as in over 1,1000 times in the dataset and that there are not just a couple words driving results.

Not every word in the dictionary appears in the corpus, which is normal. For the positive dictionary, 49.56% of the words appear in the corpus and it is of the negative dictionary 44.68%. This is not unexpected; the corpus is limited in its topics and there are a limited number of ways to talk about those topics. Moreover, candidates have messages and talking points that they tend to stick to which would limit the number of words that they would use in any given communication.

Figure 5-5: Density of Negative Words Across Corpus

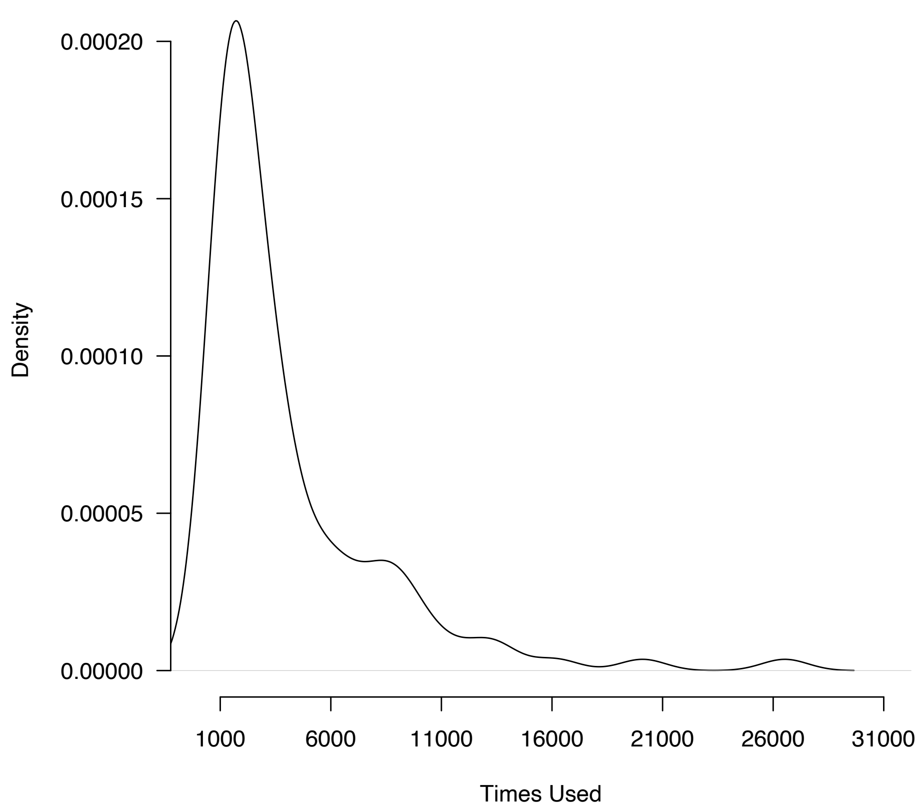


Figure 5-6: Density of Positive Words Across Corpus

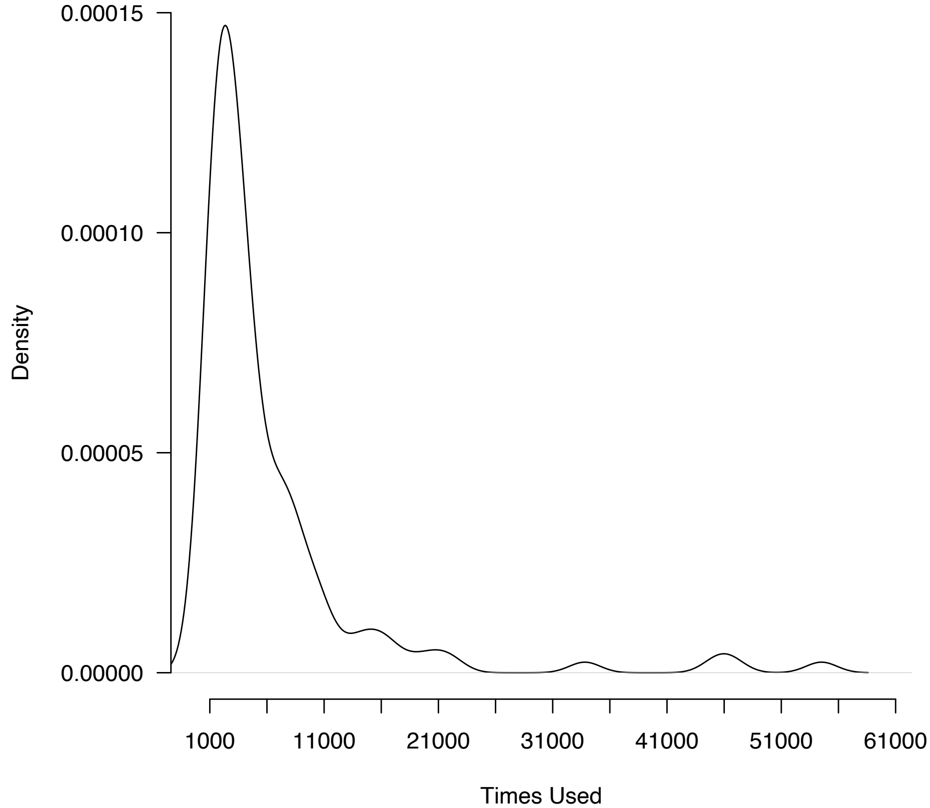


Table 5-2 below shows the top-25 most common words for both the negative and positive dictionaries plus their word count. For the negative dictionary, war stands out as clearly the most common word. However, the gap between "war" and the rest is not extreme. Similarly, for the positive dictionary we see multiple words that are being used often. One word that stands out as being notable for the positive dictionary is "great"; as in "Make America Great Again". In fact, Trump's owns 77% of the number of "great" words in the dataset. The key takeaway from these results, though, is that the main findings are not being driven by one or just a couple words, but instead by a wide range of words across both dictionaries.

Table 5-3: Top-25 Negative and Positive Words

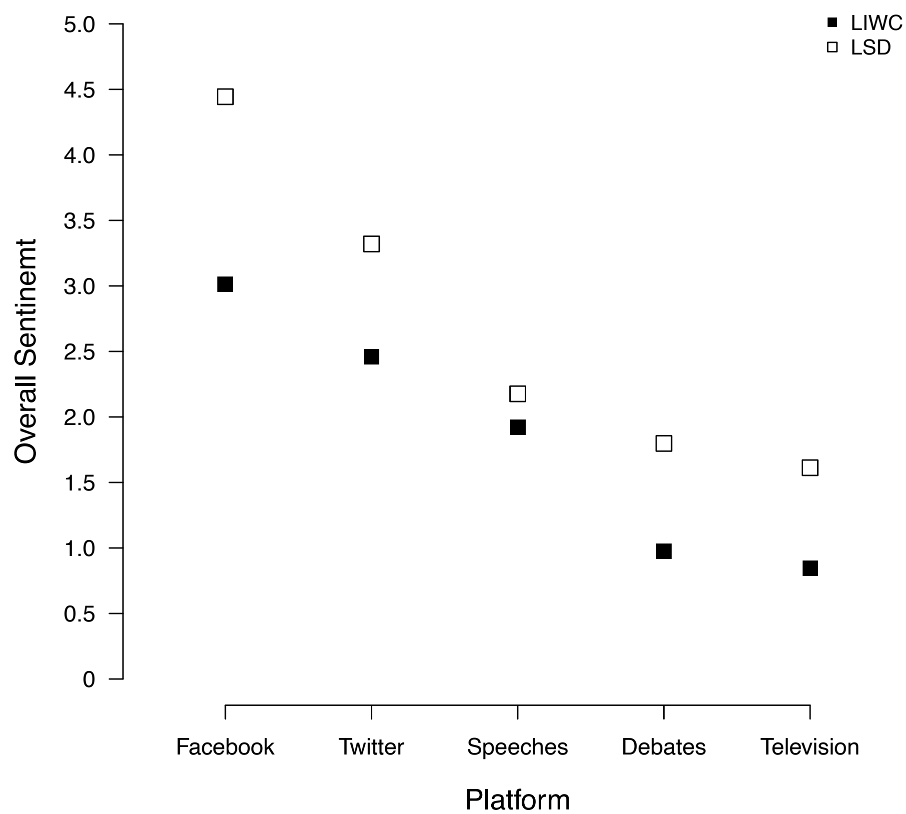
Term	Count
war	26528
hard	16163
ill	13224
problems	9534
bomb	9259
hell	9157
harder	8429
wait	7983
crime	7656
shell	7186
bad	6119
gang	4282
problem	3871
dead	3827
knock	3630
broke	3543
opposed	3217
punch	3179
crap	3160
scares	3035
flipped	2791
fear	2743
slob	2466
scare	2410
prison	2086

Term	Count
like	54520
great	46608
right	45341
care	33808
good	20839
well	19208
safe	15285
better	15070
create	13654
love	13448
fair	10993
join	10700
thank	10696
provide	9888
best	9836
trust	9565
okay	8591
hero	8541
win	8478
special	8174
respect	7916
stronger	7796
secure	7587
strong	7567
rights	7083

Alternative Measures of Sentiment

Another way these results may be biased is due to the choice of dictionary and that the results are dependent on the specific sentiment words included in the LSD. While the LSD has been rigorously tested, it is useful to verify these findings with other dictionaries. To do this, I compare another commonly used dictionary in content analyses; the Linguistic Inquiry and Word Count's negative-positive dictionary, henceforth LIWC, (Pennebaker et al., 2001). There are certainly limitations to using LIWC, though. It is a smaller dictionary and contains words that are relatively more subjective in their inclusion. Nevertheless, it is an important test of the LSD scores presented above. Figure 5-7 below shows the results of the LIWC dictionary compared to the LSD, using the same simple means method described above.

Figure 5-7: Comparing LSD and LIWC Across Platforms



I find almost the exact same relationship between platforms and content. The most negative platforms are television ads and debates. Facebook and Twitter are relatively more positive. Speeches are around the middle of the group. All pairwise comparisons using a Tukey test are statistically different at $p < 0.001$ with the exception of television ads - debates. I view this as strong evidence that my findings on sentiment are robust across multiple dictionaries.

Again, throwing out Kasich and Sanders from the debate and television corpora, respectively, leads to sentiment scores of 0.924 for debates and 0.621 for television. These differ significantly at $p < 0.005$.

Table 5-4: Pairwise Tukey Tests of Mean LIWC Sentiment Across Platform

	Difference	P adj.
Facebook-Debate	**2.037**	**0.000**
Speech-Debate	**0.948**	**0.000**
Television-Debate	-0.129	0.621
Twitter-Debate	**1.485**	**0.000**
Speech-Facebook	**-1.089**	**0.000**
Television-Facebook	**-2.167**	**0.000**
Twitter-Facebook	**-0.552**	**0.000**
Television-Speech	**-1.077**	**0.000**
Twitter-Speech	**0.537**	**0.000**
Twitter-Television	**1.614**	**0.000**

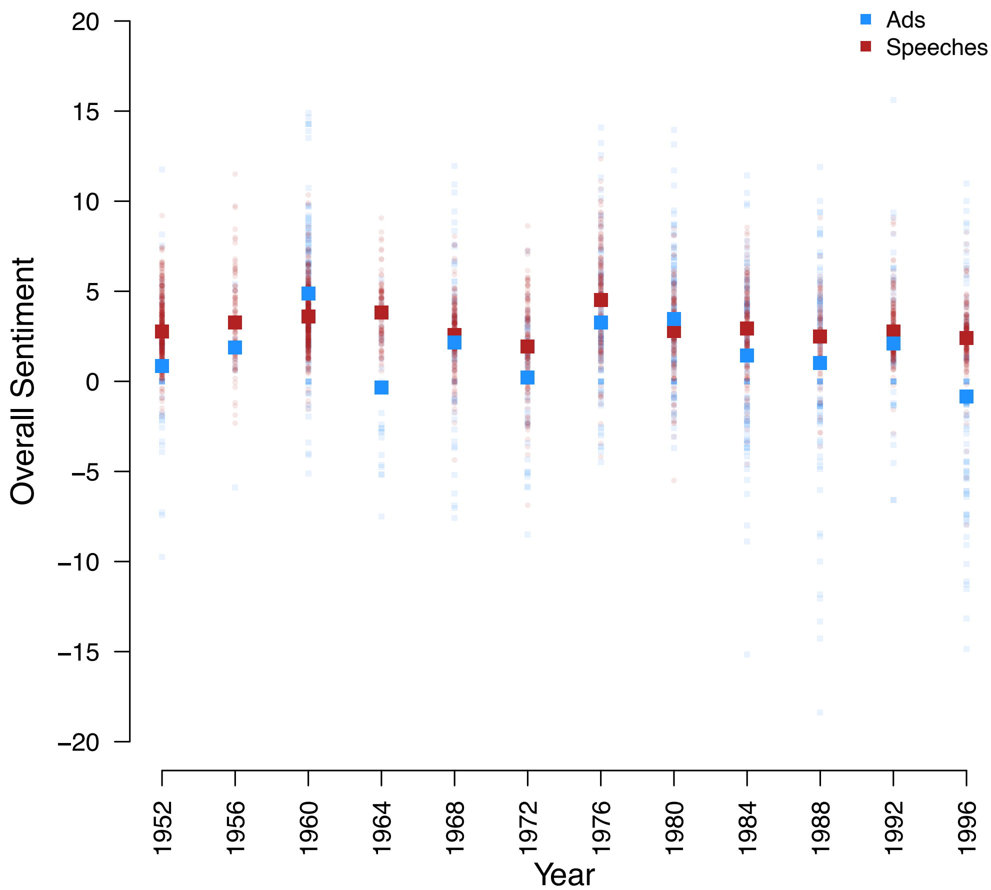
Beyond the 2016 Election

Another concern for my results is that they are predicated on the 2016 election being an abnormality in how sentiment was used. The 2016 election certainly felt different from others in recent memory, at least anecdotally. Yet I would argue that the campaign communications themselves were not fundamentally different from others. In order to test that claim, I also looked at the possibility that my findings are just a result of this specific election.

I look at the 1976 election between Carter and Ford using the Annenberg/Pew Archive of Presidential Campaign Discourse (Annenberg, 2000). This dataset includes transcripts of television ads, speeches, and debates for both major party candidates between 1952 and 1996. I selected the 1976 election as it is one of the larger collections of data and is relatively evenly divided between both parties. Using the same LSD dictionary as described above, I looked at the 100 television ads and 183 speeches from the cycle. With fewer platforms, there is inevitably more overlap between content which would reduce the magnitude of the differences among platforms. Mean sentiment for television ads is 3.181 ($s = 0.373$) and speeches is 4.374 ($s = 0.205$) and they significantly differ at $p < 0.005$ ($t = -2.799$). This tells us that television advertising in 1976 was more negative than live speeches, which is the same as it was in 2016. Put more succinctly, the same relationships that I find in 2016 exist in 1976.

To add even further to this, I look at the sentiment scores across the entire Annenberg dataset. With the exception of 1960 and 1980, television advertising is more negative than debates across every year. Figure 5-8 shows these results with the large squares indicating the mean for that year for both platforms and smaller colored circles representing the datapoints within each year. While 1976 was useful in that it provided an important illustrative example, these results show that it is not an outlier, but instead indicative of how candidates deploy sentiment differently across platforms.

Figure 5-8: Sentiment Across Platform by Year 1952 – 1996



Finally, I want to ensure that my results stand up beyond the presidential race, but also for down-ticket campaigns. I do a last check on the degree to which the findings are limited to the presidential campaign only by looking at congressional Twitter and Facebook content. To do this, I looked at the mean sentiment for 697 Twitter accounts and 569 Facebook accounts of congressional candidates from both parties during the 2016 campaign. These were acquired in the exact same way that the presidential data was and is bounded by the same time constrains and data limits.

This dataset totaled 546,067 Tweets and 228,316 Facebook posts between January 1st, 2015 and November 9th, 2016. Candidate Twitter accounts tweeted about 783 times per account and have a mean sentiment of 4.069 (SD = 10.388). This roughly lines up with the sentiment for the presidential candidates on Twitter, which is 3.589 (SD = 10.027). Facebook users posted an average of 411 times. Sentiment for congressional Facebook campaigns was 4.879 (SD = 8.304). This, again, is comparable to sentiment for presidential posts, which is 4.444 (SD = 9.805).

These findings present evidence that my main results mirror historical elections and are not a function of the vicissitudes of the 2016 campaign. Further, I find that it is not just at the presidential level that these findings hold true, but also at the congressional level for at least the *narrow* audience, *shared* channel platforms. While I do not have data for this election for television ads, there are reasons to suspect, given the literature highlighted above, that congressional television advertising is more negative than their *narrow* and *shared* channel communications are. Finally, looking back at the totality of the robustness tests, I view this as strong evidence that the predictions made by the PACT are supported.

Discussion

Political campaigns are a time of increased political information and increased voter attention. Candidates seek to get their message out through a multitude of different communication platforms, but because these platforms differ by their technical features and user affordances, the content itself must differ. If that is the case, then we ought to expect differences in content across platforms in predictable ways. For political candidates looking at the communication ecosystem, they must consider the channel and audience of each platform. Channels inform them of the degree to which they can directly criticize their opponent as well as be criticized. The degree of diversity in political affiliations and candidate support is the audience of the platform, and also shapes what a candidate says.

In this chapter, I looked at tone, or the use of positive or negative language. I expect tone to become more negative on *independent* channel, *broad* audience platforms, whereas *shared* channel platforms with *narrow* audiences will be more positive. Looking at the 2016 US presidential campaign, I find that tone is indeed more negative for *broad* audience, *independen*t channel platforms, such as television advertising, whereas *narrow* audience, *shared* channel platforms, like Facebook and Twitter, are much more positive. These findings are relevant not just to the 2016 campaign, but also to campaigns in the past and future. I support my findings with an example of 1976 election and congressional races; the LIWC dictionary; and robustness checks on the language being used.

And as new communication platforms emerge, their placement on the channel and audience dimensions can lead us predictions about their tone. The theory set out above offers future researcher a powerful tool for understanding certain aspects of new platforms quickly and efficiently. This is to my knowledge the first large-scale empirical test of cross-platform campaign communication. The typology set out here would of course benefit from further testing, across both space and time. I undertake an investigation into policy language in Chapter 6, but there are many other kinds of content that scholars have identified as being important to political communication, such as content that focuses on issues of gender, race, and group language (e.g. Dolan, 2005; Mendelberg, 2017; Budesheim et al., 1996). Understanding where and when these, and other, kinds of content are deployed is also important to broadening scholarship on political campaigns. What I hope this project, starting with this chapter, does is highlight empirical confirmation of the value of the Platform Audience and Channel Theory as an explanatory tool for content across platforms.

If it is the case that platforms contain systematically different content, as we see here, then citizens may be differentially exposed to political content. This may have downstream effects on their evaluations, attitudes, preferences, and behaviors. It is not impossible to imagine an individual who only gets their information from television advertising as having a significantly different evaluation of candidates and the campaign as a whole than someone who gets their information from debates or Twitter or another place, for instance. This is a critical implication of the findings presented here. As an increasing number of communication platforms offer increasingly differentiated content, we should expect more heterogeneity in what individuals know about, and how they respond to, political campaigns. In the next section I look at policy content across platforms and draw connections between policy and sentiment.

Chapter 6 Policy Across Platforms

During the 1988 US presidential campaign, Republican nominee George H. W. Bush aired television advertisements featuring footage of his opponent, Michael Dukakis, riding around in an M1 Abrams tank. Dukakis is wearing a protective helmet and has a facial expression which, while ridiculous, is one that I can only imagine almost any person would have on their face the first time they are riding around in a 60-ton vehicle. Yet the ads that Bush aired are clearly a condemnation of Dukakis as being weak on defense and national security while using the visuals to ridicule Dukakis for the way he appeared in the footage. More to the point: while the ad partly focused on how Dukakis looked, it also contained policy cues. By bringing up how Dukakis might perform as Commander-in-Chief, the Bush campaign was questioning their opponent's credentials, and also potentially highlighting Bush's experience as the director of the CIA. Even as some of this was not explicitly stated, there were still clear policy cues within the advertisement, and voters could use those cues to form evaluations of the country and the race.

Political communications often contain policy references, sometimes explicitly and sometime implicitly. Some of the most famous and commonly cited examples are the Daisy Ad (in which Lyndon Johnson's campaign suggested that a Barry Goldwater presidency would lead to nuclear war) and the Willie Horton Ad (where the Bush campaign attacked Dukakis, again, for a prison furlough program that resulted in the escape and subsequent violent crimes of William Horton). While the veracity of these claims made in the ads is suspect, they clearly signal policy positions. And this policy information plays a crucial role in educating the populace about the current state of issues, as well as drawing distinctions between candidates. It is, consequently, important to understand when and, more importantly for this project, where policy language is deployed.

This chapter focuses on the presence and/or prevalence of policy-related content in campaign communication. By policy-related content, what I mean is policy language or words that explicitly describe issues of public policy in substantive ways. For instance, candidates who talk about honoring commitments to NATO would be considered as using policy language. Conversely, a politician calling their opponent a "baby-killer" would not qualify. While ostensibly about a public policy issue, abortion in this case, the phrase is principally a negative attack. While policy language can be clear and straightforward or suggested and implied, for the purposes of this chapter I am only concerned with clear and explicit policy language. The Willie Horton Ad had clear policy language in it; as did the Dukakis Tank Ad. The Daisy Ad, however, does not by my specification when we consider the *text* of the advertisement.[8]

To use a specific example relevant to my dataset, Vavreck and Geer found that Bernie Sanders' "America" advertisement was one of the most positive emotion-inducing ads in the 2016 campaign (Vavreck, 2016). However, the advertisement contained no policy words, mentions of policy, or even explicit policy images. There may indeed be vague references to policy, or an individual could read policy cues into the images, but for the purposes of this chapter that advertisement was not policy related. Contrast this with Sanders' candidacy announcement speech where he includes the line "Let me be very clear. There is something profoundly wrong when the top one-tenth of 1 percent owns almost as much wealth as the bottom 90 percent, and when 99 percent of all new income goes to the top 1 percent." This is clearly about policy and would be coded as such for the analyses that follow.

[8] Note that I look at visual and nonverbal information, which the Daisy Ad has, in Chapter 7.

Some of the examples above make clear that policy and attack ads are frequently one-in-the-same, suggesting that the relationship between the two may be of. I accordingly also look at the relationship between policy and sentiment, examining where negativity and policy language co-occur. This chapter begins, however, by reviewing the literature on why policy language matters, and considering how politicians use policy language throughout their campaigns. I then outline some expectations for policy language across platforms based on the PACT. Finally, I examine policy language, and the relationship between policy and sentiment, in my corpus.

Why Policy Matters

Policy language is a fundamental information source for voters about both policies and candidates. One way it accomplishes this is through learning about policy through agenda-setting and priming. That is to say, policy language shapes the discourse around a campaign and is suggestive of what is relevant to the election. That relevance may come from the role of policy language to activate economic fundamentals. This is a vital component of informing voters; especially during campaigns when many are paying attention. Lastly, policy language functions as a method of accountability within a representative government. It can serve as a cue for citizens about the state of the economy and the level of social policies. The roles that policy language plays are central to a functional democracy, and thus underscore the importance of understanding where citizens get policy cues.

To be clear, the effect of policy language may not be one of persuasion as much as agenda-setting or activation of priors. As Arceneaux points out, campaigns use policy information primarily as a reinforcement and reminder mechanism as opposed to a persuasion one (Arceneaux, 2006). While these effects may be short-lived (Gerber et al., 2011), they exist and can have influences on the electorate. Using policy language, then, is associated with candidates attempting to set the agenda for a campaign (Boydstun et al., 2013). In so doing, they can try to shape the narrative of the campaign, ideally in a positive light for them. This is easily noticeable when viewing a debate, where candidates will seek to shape their answers around their specific policy beliefs, whether that is Medicare For All, UBI, or deregulation. This may lead to voters remembering these specifics policy proposals and/or news media focusing on the candidate's ideas. A candidate that can force the narrative of the campaign into something that they excel at or are seen as being better at, give themselves a potential electoral advantage (Roberts & McCombs, 1994; Conway et al., 2015). This is especially important when we consider the literature on issue ownership. Scholarship in this field has told us that the major political parties "own" different policies, as in they are seen as being better at them than their counterparts (Petrocik, 1996; Petrocik et al., 2003). By making a campaign about a policy that the party is seen as being better at and by forcing other candidates to respond to these issues, there is potential to increase attention and possibly vote share.

This is not abstract; indeed, a topical example comes from the 2020 Democratic presidential primary season where Governor Jay Inslee spent an entire debate talking almost exclusively about climate change. In so doing, he was able to force other candidates to respond to his arguments and policy positions, forcing the debate as a whole to be more focused on the issue that he had made central to his campaign. What was even more telling is that the debate the night before, with the other half of the Democratic hopefuls, barely talked about climate change. While his candidacy ultimately ended, the debate itself served as an important reminder of how a candidate can deploy policy language to their personal electoral advantage.

Policy language gives voters important cues as to the state of public policy and what has happened recently. They use these cues to form important impressions about the direction the country may go depending on who wins the election. This is especially important for economic conditions, which have been linked by numerous studies to predictions about the outcome of elections (Fair, 1978; Abramowitz, 1988; Lewis-Beck & Stegmaier, 2000). Moreover, by simply talking about that state of the economy, and the degree to which related policy positions have helped or hindered economic conditions, candidates can use policy language to prime voters to do these retrospective analyses of economic conditions (Vavreck, 2009). Thus, when politicians speak of policy or political processes, they are providing critical information to voters which is used to form evaluations of candidates themselves (Blais & Perrella 2008; Trammell 2006; Benoit & Hansen 2004).

This may be especially important for low-attention voters who might only tune in for debates, conventions, major addresses, or are incidentally exposed through television advertising. Because there may not be much else to go on, for voters who have an absence of political cues in their information ecosystems, the policy signals that they do see may be more heavily weighted when they are received, such as party ID, race, gender, and occupation (McDermott, 1998; Schaffner & Streb, 2002; Matson & Fine, 2006). Consequently, if there are platforms which are systematically producing more policy language, then those low-information or low-attention voters who primary use that platform would be receiving more information to act on than their counterparts on other platforms.

Much of the literature on policy language I outlined above is focused on economic conditions, as is appropriate given the outsized effect that economic indicators have on the outcome of elections (Markus, 1988; Erickson, 1989; Lewis-Beck & Stegmaier, 2000; Lockerbie, 2012). However, there are other policy domains that serve important mechanisms for voters. Druckman (2004), for instance, finds evidence that campaigns can draw the attention of voters to issues that the campaign is making important in the election. Valentino et al. (2004) also point out that learning occurs during campaigning, even if much of the accurate learning occurs among the most aware of voters. The important takeaway here is that attention to and learning about policy can and do occur in a wide range of policy domains, not just economic ones.

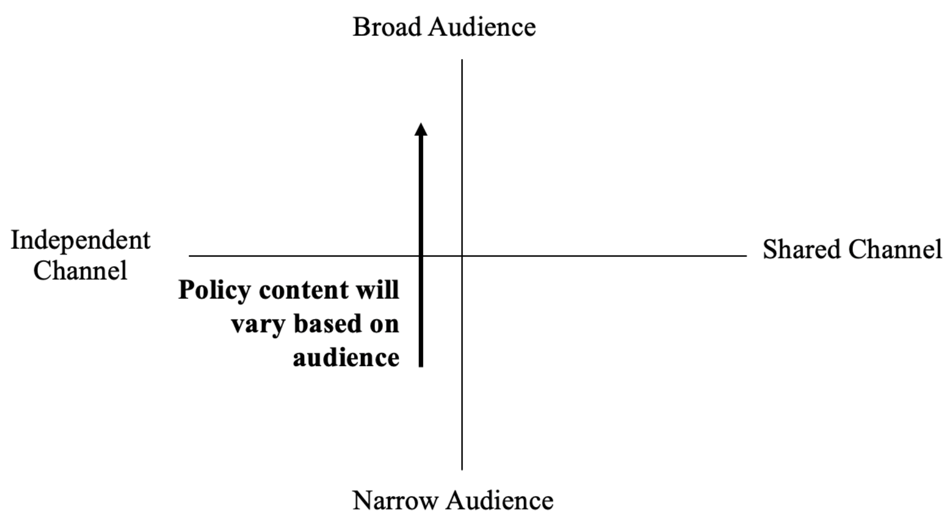
This leads into the importance of cues as a way for citizens to hold governments and politicians accountable. There is a great deal of literature on the importance of policy cues as the mechanism by which voters to stay informed about current affairs and policy positions (Wlezien & Erickson, 2002; Ansolabehere & Iyengar, 1997; Gelman & King, 1993). By learning about policy, voters are able to make distinctions and judgements about the state of the country. When governments fail to meet their policy promises there are electoral consequences (Downs, 1957; Naurin, 2011). Thus, policy cues are vital for citizens to learn about the state of government and who to hold accountable for successes and failures. Together, these form vitally important mechanisms for voters to hold their governments accountable as well as form impressions of those running for office. As a representative and accountable government is dependent on a sufficient number of policy cues, where those cues are coming from and on which platforms is of vital concern (Neuner et al., 2019; Hiaeshutter-Rice et al., 2019).

The effects of policy language, thus, are setting the agenda for what the campaign is about, activation of economic conditions, as well as evaluations of candidates and their policy positions. Further, the effect of exposure to policy language has been linked to voting and evaluations of where the country and policy levels are at. I argue that it is highly consequential, then, to understand which platforms produce more policy content than others given what I have outlined about exposure to policy information.

Expectations

Given the vital role that policy language plays in elections, I want to use the Platform Audience and Channel Theory to build a set of expectations about the relationship between policy and platforms. To reiterate, the PACT's fundamental argument is that differences in content is driven, in part, by the audience and channel of each platform. I predict that *broad* audience platforms ought to contain more policy language than *narrow* audience platforms. That means that television and debates will have more policy language than Facebook, Twitter, or speeches. I use Figure 6-1 to illustrate the relationship that I expect for policy language.

Figure 6-1: Visualized Policy Hypothesis



In order to flesh out these expectations, I rely on a body of literature that is closely related, but not fully focused on, the role of policy language on platforms. Much of this work is centered on the psychological processes involved in communications, which is important, but not exactly similar to what I am accomplishing here. Therefore, the foundations of my hypotheses are based in literature, but also driven by my interpretation and suppositions about how policy language is used.

I argue here that audience is the relevant component of the PACT for policy cues. Why audience and not also channel? I posit that campaigns are structured around policy: candidates hold policy positions, they advocate for their issues, and use those policies to distinguish them from opponents. Broadly speaking, the literature reviewed above would suggest that candidates can use policy language to mobilize voters or persuade voters. These are simplifications, to be sure, but encompass the wide range of effects of policy on voters. The deployment of policy language is more dependent on a match with audience than engagement with opponents, then, because the goals of policy language may not be contingent on the degree to which candidates can interact with one another.

I should clarify here that, while campaigns are structured around policy, it is not necessarily the case that politicians make their campaigns *about* policy. Candidates may use a wide variety of tools to communicate with voters. There are policies the candidate holds, personality traits they want to highlight, backgrounds that are important, and attacks to be made. However, what I want to make clear here is that a *single* policy, or small set of related policies does not automatically equate to communications being universally organized around that policy. Campaigns which cover a wide range of topics are, in my estimation, far more common than those who centrally organize around policy communications (and something that I test below). Some do, of course. Anecdotally, in 2016 Bernie Sanders made his policies the key motivation behind his candidacy and the organizing structure of his constituents. He did the same in 2020, as did Elizabeth Warren. For these campaigns, and others, the policies are the reason to mobilize, donate, and vote. More relevantly, these campaigns may make communicating about policy central to their communications strategy. I devote time to this because campaigns which have a multitude of goals and communications they want to get out are making strategic decisions about where to do that. This section sets out the expectations for which platforms best fit the goals of policy communication, and thus where we ought to expect to see it.

To start, I expect that platforms with *broad* audiences will contain more policy language than *narrow* audience platforms because *broad* platforms are well suited for agenda-setting and candidate comparisons. Television is a *broad* audience platform, so candidates who air ads are able to communicate to a large number of potential voters. Candidates can use policy language to link themselves to issues that voters care about (Just et al., 1999). This also allows campaigns to reach out to voters who may not necessarily have interest in campaigns and politics to remind them of what the election is about. Returning to the issue ownership and campaign agenda setting literatures, there are also reasons to suspect that campaigns will use *broad* audience platforms to promote their issue agendas. In so doing, they may be able to reach those voters who are persuadable or are supporters but less likely to vote. There is even evidence that most ads on television would qualify as an issue ad (Johnston & Kaid, 2002). The benefits of a *broad* platform means that issue language may have a greater influence and reach than other platforms, incentivizing its usage there.

This is notably important as other forms of information sources, newspapers, television news broadcasts, and information mediated through websites and other actors may not necessarily connect policy positions to a specific candidate. When a politician airs an advertisement on television, they can share their policy views directly with a large audience, thus taking credit for their ideas without mediating influences. Of course, they can do the same on a *narrow* audience platform, and indeed some literature does focus on the agenda-setting capabilities of platforms, especially Twitter (Conway et al., 2015; Skogerbø & Krumsvik, 2015). However, the evidence on agenda-setting in narrow platforms, specifically social media, is that they operate through an intermedia relationship. That is to say, agenda-setting often functions through other actors amplifying the messages of a candidate or campaign. This takes the message out of the candidate's hands and lets the media dictate the story. That can result in attention being drawn to their opponent and editorialization of the message (Conway et al., 2015). A *broad* audience platform, such as television, allows for an unadulterated message to reach voters.

The other *broad* platform that I investigate here, debates, would certainly allow for responses and editorializations from opponents on policy issues. This does not, in my estimation, change the prevalence of policy content on debates, though. That is because debates serve another purpose of policy language extremely well, that is drawing comparisons between candidates. Debates are a time of learning for voters, and the use of policy language allows them to learn about candidates and issues (Zhu et al., 1994). The persuasive power of a candidate discussing issues has been linked to increased evaluations of the candidate and their policy preferences (Fridkin et al., 2007). While the degree to which those evaluations last may be subject to debate, the general point is that candidates can use policy language to make an impact on voters.

Debates are one of the few major campaign events where a large and diverse number of individuals are paying attention (Kaid et al., 2000) and one of the few opportunities for candidates who are farther down in the polls to make an impression on voters. Indeed, one can see evidence of this during the 2016 campaign with Carly Fiorina. Because there were so many Republicans running for the nomination, the party split their initial debates into two events. Fiorina's initial polling numbers placed her in the "undercard" debate, with other low-polling candidates. However, her performance during the debate sparked increased attention and interest in her candidacy, which propelled her to the main event stage for future debates until she ended her campaign.

As it did for Fiorina, debates offer an opportunity for candidates to draw clear distinctions between themselves and their opponents; and they can most easily do this by differentiating their policy positions from their opponent's. Doing so requires, of course, the use of policy language. In addition, while the formats of debates vary, generally there are a set of questions and rebuttals that each candidate is faced with. This forces candidates to directly engage with what their opponents have said and leads to more policy-specific comments (Benoit & Harthcock, 1999). I expect, then, that there is more policy language in debates than *narrow* platforms where the need to differentiate is not as pressing.

Conversely, *narrow* platforms, such as Facebook and Twitter, will have fewer policy references and word usage than *broad* platforms. I should reiterate here that I do not mean that there will be no references to policy on Facebook, Twitter, or speeches, but there will be less than television or debates. This is because candidates view the purpose of these platforms differently (Kreiss et al., 2017; Kreiss, 2016). Instead, *narrow* platforms are about mobilization and shoring up co-partisan support. Some of that requires policy language, but much does not.

When candidates do use policy language on *narrow* platforms, it is not necessarily the case that the policy content there matches what citizens are most concerned about (Adams & McCorkindale, 2013). This suggests that the purpose of social media, in the eyes of candidates, is different than pushing policy agendas. Moreover, there are studies, both in the international context and for the U.S. specifically, which find that candidates seldom use Twitter for policy purposes (Graham et al., 2013; Bode et al., 2016). In part, that may be due to Twitter being used to speak to existing supporters as opposed to a broad range of individuals (Kreiss, 2016). Instead of using Twitter for policy, they use it to discuss other issues, themselves, and ask for engagement. These findings reinforce the idea that the platforms are being used strategically, and in different ways.

If candidates are not using *narrow* platforms for policy content, then what might they being using it for? This speaks to a broader trend in political campaigning, which is the move to personalized politics (Bennett, 2012; Holtz-Bacha et al., 2014), which incentivizes insights into a candidates personal life and personality. For instance, in the 2020 primaries, Elizabeth Warren posted a video on Instagram Live in which she was drinking a beer on in 2016 Bernie Sanders engaged in basketball games with staff and reporters during his candidacy. The point of those presentations is that they open up the candidate to be viewed as more than simple policy positions and partisan talking points. That glimpse into their personal life is a way to connect with core supporters to engage their involvement in the campaign and invest resources. These are not necessarily suitable for television or other *broad* audience platforms.

As far as speeches go, my argument is that they are functionally similar to Twitter and Facebook as far as policy language. There is personalization in speeches, the anecdotal example being how often a candidate would thank their spouse, kids, etc. in a speech. There is also an incentive to push engagement and encourage attendees to volunteer, donate, and vote. Simply put, speeches are designed to rally attendees into action, not necessarily push policy agendas. Having said all of that, for policy language, I predict that:

H1: Broad audience platforms (television ads and debates) will have, on average, more policy words than narrow audience platforms.

The existing literature supporting H1 is, I admit, a little light. As noted above, this is primarily due to the gap in scholarship on the deployment of policy language. However, there is a related set of literature that I turn to in the next subsection which I view as bridging Chapters 5 and 6, while also providing some justification for H1.

Policy and Sentiment

Having described why we ought to care about policy above, and sentiment in the previous chapter, I want to spend some time investigating the relationship between the two concepts. To that end, it is possible that tone and policy are not orthogonal; specifically, that negativity is used to highlight the differences between candidates and that we ought to expect that negative tone and policy language go hand-in-hand often. Geer argues that negativity serves a function in a democratic election (2008). Attacking statements can serve to "set the record straight" about an opponent by criticizing their record on policy and positions (Geer & Vavreck 2014). This means that candidates, when talking negatively about their opponent are also likely using policy language; thus, serving to inform the electorate of important policy topics. That negativity and policy language covary is an important component of understanding platform differences. Platforms where candidates are more negative are likely to also include more discrete cues about policy.

I covered the role that sentiment plays in user attention in the previous chapter, but briefly: platforms which are comparatively more negative are likely to draw more attention from users (see Ito et al., 1998; Soroka et al, 2019). We also know that information is vitally important for citizens to hold governments and leaders accountable (see citations above). When we think about political communication and the democratic role that it plays, understanding which platforms might best serve that role is a crucial and underdeveloped area of study. In order for a platform to be well suited for enabling democracy, it must both get the attention of users and also provide cues about policy and politics. Given the discussion about sentiment and policy, I predict that:

H2: A broad audience, independent channel platform (television ads) will have the most policy language and be the most negative of all platforms.

The next section describes how I coded for policy language and then moves to results.

Capturing Policy Language

To code for policy words, I use dictionary-based processing using a self-developed dictionary. I start with the Lexicoder Topic Dictionary (Albaugh et al., 2013). This is a list of 1,397 topical words and phrases that include “aggregated demand,” “NATO,” and “prison.” This is an excellent place to begin but has some limitations for my purposes; the most important of which is that it was originally designed for the Canadian political context and as a comparative tool. I accordingly modify the dictionary extensively to ensure that it captures US policy by starting with removing any references to Canadian specific political institutions, systems, organizations, etc. I also strip out words that do not have clear policy connections. I am left with 860 items including topics like “Medicaid,” “voter registration,” and “refugee.” The intention here is to create a dictionary of words with clear connections to policy domains. While certainly not an exhaustive list, this dictionary covers a great deal of policy content that one might reasonably expect to come across in a campaign. I use two scores for policy words, the first is a binary classification as follows:

Binary policy: 0 no policy words present – 1 any number of policy words

For example:

> “**Medicare** spending growth is placing an inescapable burden on future generations.” – *Chris Christie (November 2015, tweet)*

This text contains a policy word, Medicare, and would be coded as a 1. Overall, 52.70% of all observations have at least one policy word in them. The second measure that I will discuss is the percentage (which I also call volume) of words within each communication that are a policy word. I code this measure:

*Percentage policy: (# policy words / total # words) *100*

Again, the quote from Christie's Twitter account would contain one policy word and has 11 words in it. That observation would be coded as (1/11)*100, or 9.09%. Mean policy words for the entire dataset is 1.926% (SD = 2.965) — that is, in every 100 words, there are on average close to 2 policy words. Median policy words is 1.030%. For sentiment, I use the same approach that is described in Chapter 5.

I want to focus the following analyses on the presence of policy language instead of percentage. I take this approach because the argument about policy language I laid out above is about if candidates are talking about policy, not how many words they use to talk about it. Unlike sentiment, I argue that there is a diminishing return component of policy language. Saying more policy words does not make the communication *more* about policy, whereas saying more negative words does make the communication more negative. An advertisement that includes one mention of Medicare is the same as an advertisement that mentions it twice. One mention is all it takes for something to be policy related. While I center the analyses on the binary specification, I do look at volume as a backup as well in the robustness section of this chapter.

Results

I start with a test of H1 by looking at binary classifications for the presence of policy language across platforms. My expectation is that *broad* audience platforms, such as television and debates, will have higher percentages of their content with at least one policy word in them. Conversely, *narrow* audience platforms, like Twitter, Facebook, and speeches will have a smaller percentage of their content with at least one policy word. Figure 6-2 shows the percentage of each platform's observations which contain at least one policy word. We see here exactly what H1 predicts, that the *broad* audience platforms, television and debates, have the largest percentage of their observations with policy words, whereas the *narrow* audience platforms (Twitter, Facebook, and Speeches) have fewer. Television advertising is notably higher than the other platforms as well, with almost 80% of advertisements being policy focused. While debates only have 40.57% of observations with policy language, they still contain more policy language than the narrow audience platforms of Twitter and Facebook.

Figure 6-2: Percentage of Observations With At Least One Policy Word

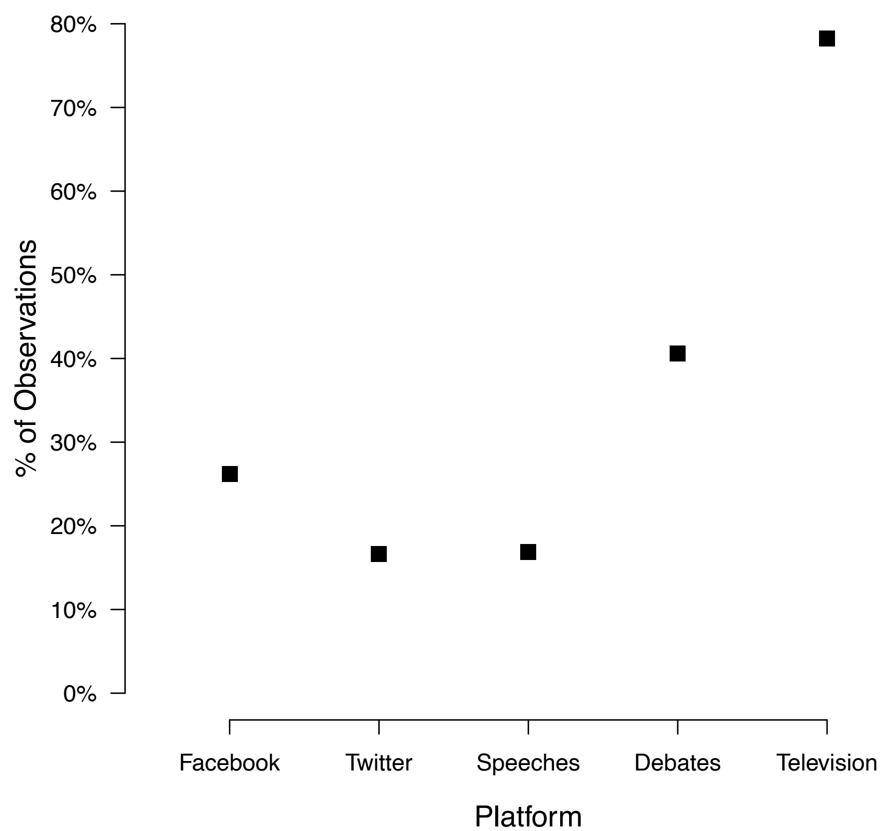


Table 6-1 presents a full pairwise Tukey test table of all of the pairings. Here we see statistically significant differences at the p <0.001 level with the exception of the Twitter-speech pairing (p = 0.894).

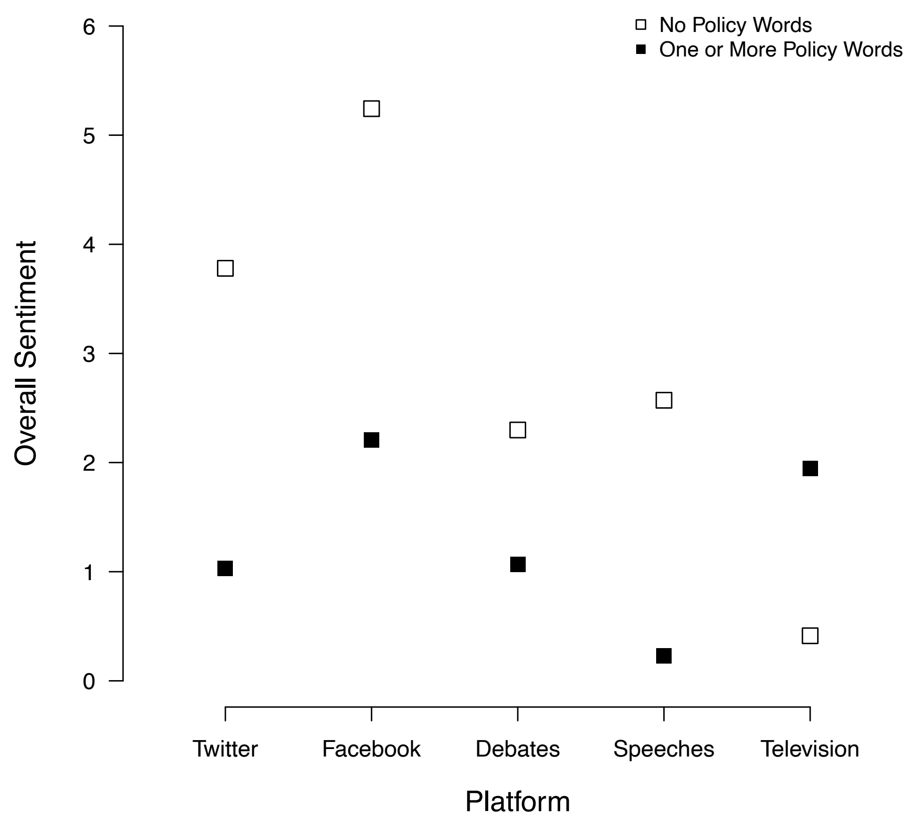
Table 6-1: Pairwise Tukey Tests of Binary Policy Across Platform

	Difference	P adj.
Facebook-Debate	**-0.144**	**0.000**
Speech-Debate	**-0.237**	**0.000**
Television-Debate	**0.376**	**0.000**
Twitter-Debate	**-0.239**	**0.000**
Speech-Facebook	**-0.093**	**0.000**
Television-Facebook	**0.519**	**0.000**
Twitter-Facebook	**-0.095**	**0.000**
Television-Speech	**0.614**	**0.000**
Twitter-Speech	-0.002	0.894
Twitter-Television	**-0.616**	**0.000**

Policy And Sentiment Results

Recall Geer's argument 'in defense of negativity,' namely, that one advantage of negativity is that it serves to highlight differences between candidates while clearing the record between competing claims. One implication of this argument is we should expect policy content to covary with negativity. I hypothesize that, when there is policy language in a communication, the content will also be more negative than when there is not policy language. I extend this in Figure 6-3 by looking at policy content in conjunction with tone by comparing the sentiment scores for each platform when there are no policy words within the observation and when there is at least one. Figure 6-3 represents this relationship with the solid square points indicating mean sentiment when at least one policy words are present and the empty squares showing the mean sentiment when there is no policy language.

Figure 6-3: Sentiment and Policy By Platform



Here we see significantly different sentiment scores within platforms when there are policy words and when there are not ($p < 0.001$ for each comparison). These findings suggest that policy and tone do, indeed, covary. As candidates use more policy language, they are also using more negativity in their communications. When policy is being discussed the platforms are all relatively clustered together on their sentiment scores, with about a 1-point range between each source. Yet when there are no policy words, there is a wide divergence for many of the platforms. Facebook is, again, the most positive of the group; television is markedly more negative. This is also important as it (mostly) replicates Geer's findings (2006) and provides confirmation of the validity of my own results.

Television is the only platform which actually gets more positive when the speaker includes policy mentions. These results are interesting as the one platform that Geer talks about in his argument is television – here, it is the only platform that does not match his claims. One potential explanation, albeit a post-hoc one, is that in this campaign negative television advertising is mostly about the other candidate's personality, history, or credentials whereas personal policy advertising on tv is about one's own policies. That is a possibility, and perhaps one that is limited to the realities of the 2016 candidates. By that I mean, there was more of a focus on the non-policy related aspects of the frontrunners of both parties. However, with the exception of Cruz, Fiorina, O'Malley, and Rubio every candidate was more positive when talking about policy than when they were not. Other explanations, such as primary vs. general election timing do not change the results, neither does looking solely at Trump and Clinton. At least in 2016, policy-related content is more positive on television compared to non-policy content. This suggests that television simply functions differently than other platforms with policy and negativity.

It is nevertheless the case that there are clear differences in tone when candidates talk about policy than when they do not. This is true across all platforms, but also in the corpus as a whole: mean sentiment across the whole database when there is no policy language is 2.609 (SD = 10.953) compared to sentiment when there is policy language, which is 1.795 (SD = 5.471). Television ads are an interesting outlier, and worth further consideration, perhaps alongside ads from previous elections.

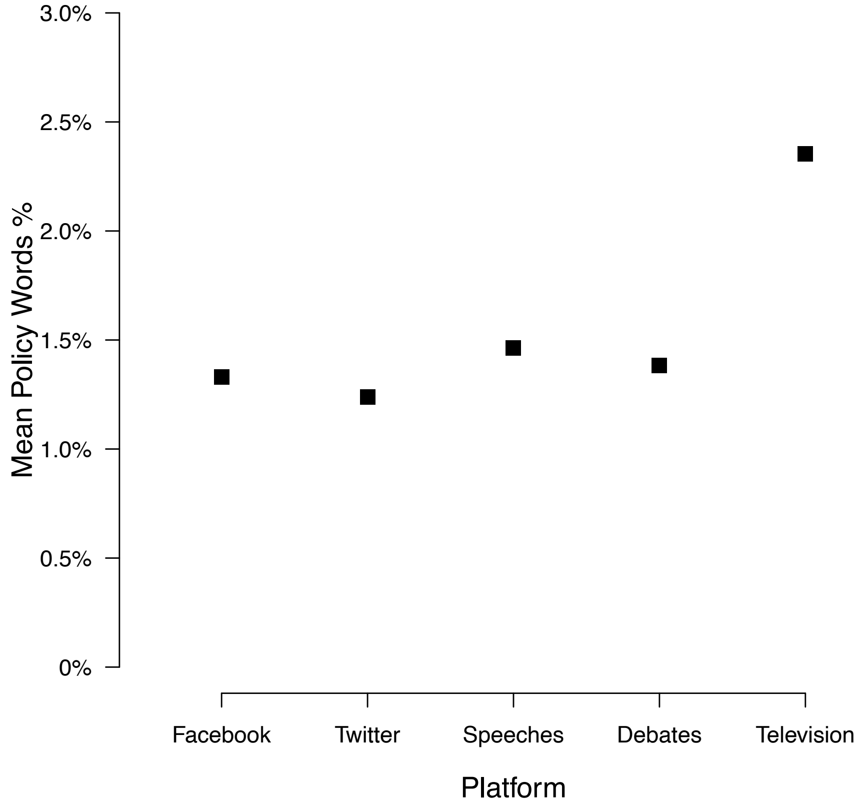
Robustness Tests

The following section looks at various other tests to flesh out the results discussed above. I first look at policy volume as opposed to presence. I then turn to alternative measures of policy language, the distribution of words in the corpus, and finally results from down-ticket races.

Policy Volume

I use this section to look at policy volume, or the average number of policy words per observation. This is different from policy presence and is the second measure described above. While I do not consider this measure to be the most pertinent to how policy language is used, it is still interesting to understand how much policy language is being used and which platforms have to the most. There are slightly different results when we look at mean policy language as opposed to the presence of policy language. Figure 6-4 shows these results. What we see is that television is still the platform with the most policy words, debates, speeches, Twitter, and Facebook are all similar in their word usage.

Figure 6-4: Mean Policy Words By Platform



Debates in this specification do not distinguish themselves from the *narrow* audience platforms. One explanation may be that debates have artificially imposed constraints on how often candidates can say policy words. By that I mean that a candidate must balance their responsibility to respond to what others say with their own desire to say things. Unlike any other platform in the dataset, they do not have full control over what they say, which may limit the number of times they can say policy words. Nevertheless, the primary findings align with my predictions, that at least one *broad* audience platform has more policy language than the *narrow* platforms do.

Alternative Measures of Policy

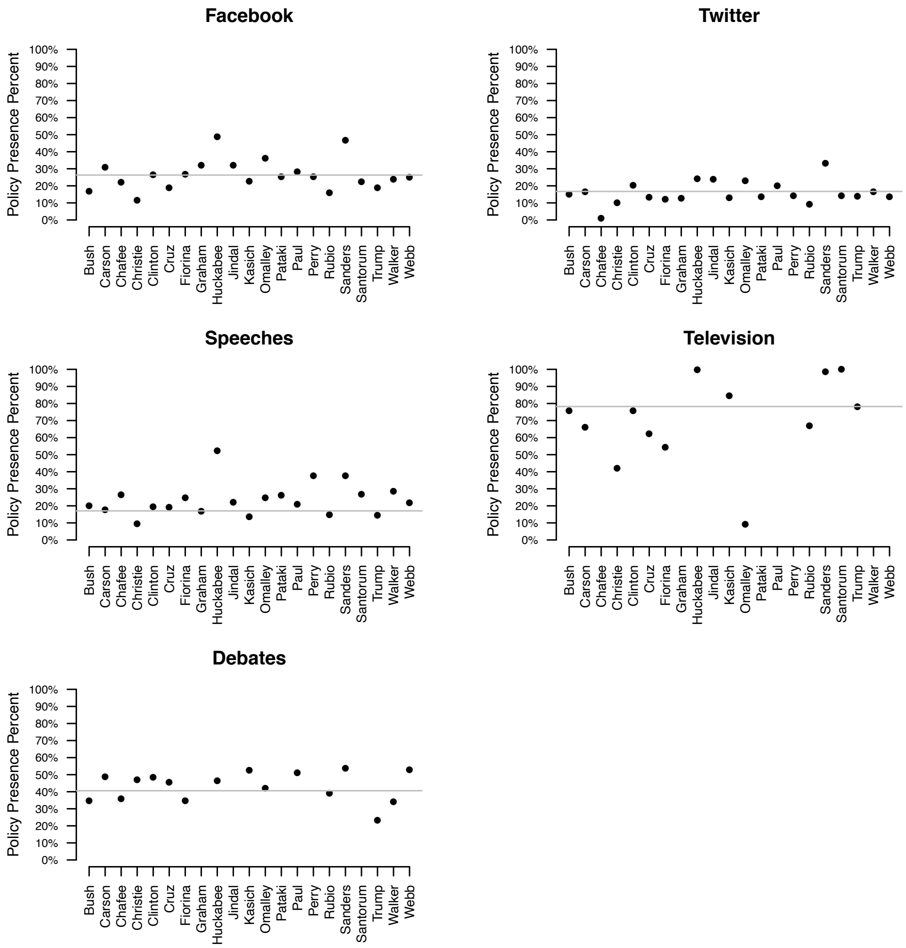
I next move to a more general policy dictionary instead of the specific one used in the initial analysis. I use a short dictionary of eight spending words instead of policy specific language. The dictionary is: "legislat*", "policy", "policies", "spend*", "regulat*", "expenditure*", "budget*", and "tax*". Spending dictionaries have been used frequently in various work and are an important cue for citizens. This is to test the possibility that, again, my results are dependent on the dictionary that I use instead of uncovering some underlying truth about the relationship between content and platforms

Here, I find somewhat similar results to using the full dictionary. Again, I use the binary specification which is the measure code 0 for no policy words and 1 for at least one policy word. This measure produces the following results: television ads are at 9.85% and debates at 10.30% while *narrow* platforms are at 4.89% for Facebook, 2.69% for Twitter, and 1.63% for speeches. All results vary statistically at $p < 0.001$ with the exception of television ads and debates, with are at $p = 0.726$. Once again, we see that the platforms with the highest percentage of observations with spending words are the *broad* audience platforms. The preceding results hold when using a smaller, more generalizable policy dictionary.

Policy Dictionary Counts

Similar to tone, policy language is not uniform across candidates. Indeed, there is some degree of variation amongst candidates in each party. Figure 6-5 shows the presence of policy language across platforms by candidate. We see here that candidates are for the most part close to the platform mean, indicated by the gray line across the figures. There are exceptions, of course, but the overall trend is that candidates are fairly often following the same trends across platforms. For some of those exceptions, which are notable in the television corpus, it is primarily driven by the low counts of television ads that candidate ran. O'Malley, for instance, only had 11 airings of his advertisements in the dataset.

Figure 6-5: Candidate Policy Presence Across Platforms



Since candidates seem to be behaving somewhat similarly across platforms, I also look at the words that were actually used by the candidates. This is to test the possibility that there are only a few words that are driving these results and not a wider range of them. Once again, I include a density plot of words that have over 1,000 uses in the entire corpus. If results were being pushed by a word or two, what we would see is a distribution with a very flat line extending outwards. Instead, what we see is the expected Poisson distribution, with a reasonable number of words being used 1,000 times or more. The most common words used are: jobs, wall, war, taxes, and health. These are included in Table 6-1. This tells us that, while many words are used infrequently, there are a number of words that are used often by candidates and that the policy results are not driven by just a few dictionary entries.

Figure 6-6: Density of Policy Words Across Corpus

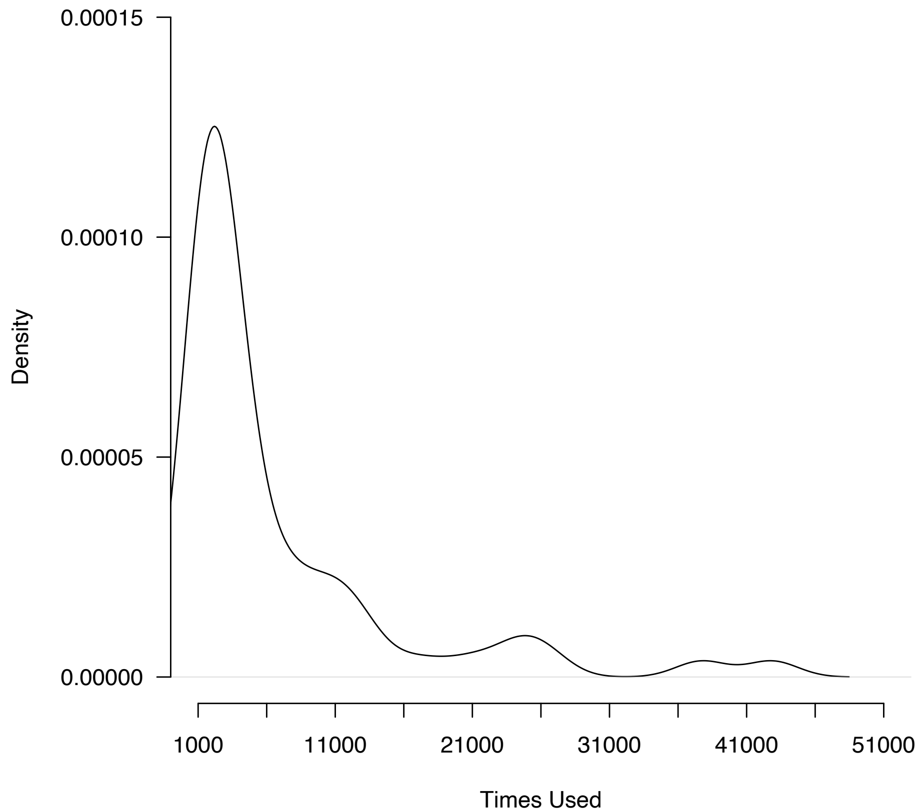


Table 6-2: Top-25 Policy Word Counts

Term	**Count**
jobs	42863
wall	37716
war	26528
taxes	25002
health	23768
tax	20748
banks	17105
government	13616
debt	12498
border	12242

obamacare	10903
corrupt	10667
wage	10494
college	9006
god	8432
crime	7656
rights	7083
student	6810
income	6206
energy	4815
justice	4702
citizenship	4532
global	4389
cancer	3807
universal	3685

As a last check on how candidates and platforms interact, I look at the results of a Type II ANOVA for both policy percentage (Table 6-3) and presence (Table 6-4) as well as the interaction between platform and candidate. For policy percentage, the whole model has a R-squared of 0.069. The sum of squares for both candidate and the interaction term are significant and account for 4.8% and 0.7% of the variance in the data. Importantly for this chapter, platform explains 1.9% of the variance and is statistically significant.

Table 6-3: Policy Percentage ANOVA

Anova Table (Type II tests)	**Sum Sq**	**Df**	**F value**	**Pr(>F)**
Platform	61146	4	1861.82	< 2.2e-16 ***
Candidate	157395	20	958.49	< 2.2e-16 ***
Platform x Candidate	21479	67	39.05	< 2.2e-16 ***
Residuals	3001439	365557		

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

We see similar patterns with an ANOVA that uses the binary specification to identify policy content. All three variables are statistically significant with the entire model explaining

32.7% of the variance. Platform has a particularly strong influence in this instance, explaining 29.1% of the variance in policy-related content.

Table 6-4: Policy Presence ANOVA

Anova Table (Type II tests)	**Sum Sq**	**Df**	**F value**	**Pr(>F)**
Platform	24442	4	39593.23	< 2.2e-16 ***
Candidate	2555	20	827.86	< 2.2e-16 ***
Platform x Candidate	458	67	44.38	< 2.2e-16 ***
Residuals	56417	365557		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Tables 6-3 and 6-4 make clear that some variance is explained by candidates, i.e., candidates differ in their inclination to mention policy. There is also variation explained by platforms, however. Platforms contain different amounts of policy content, and candidates use platforms differently. Taken together, these findings are supportive of the arguments laid out in H1.

Beyond the 2016 Presidential Campaign

Unlike with sentiment, I do not look at historical elections. The primary reason is that policy language changes so much election by election and it makes creating election specific dictionaries challenging. However, I can and do look at congressional campaigns on both Twitter and Facebook. If, as I expect, campaigns function much the same regardless of where they stand on the ballot, we would expect that the policy presence and percentage would roughly mirror that of the presidential content. Indeed, that is generally what we see in Table 6-5. Mean policy presence is the percentage of observations that contained at least one policy word, whereas mean policy percentage is the percent of all words that are part of the policy dictionary. Congressional Twitter is similar to presidential Twitter on both presence and volume. Facebook is similar as well for percentage, though there is a large difference for presence between congressional posts and presidential race posts. However, it is important to note that the congressional Facebook data is still below that of television, which is at 78.22%.

Table 6-5: Presidential and Congressional Policy

	Presidential Twitter	**Congressional Twitter**	**Presidential Facebook**	**Congressional Facebook**
Mean Policy Presence	16.71%	21.29%	26.31%	45.22%
Mean Policy Percentage	1.238%	1.572%	1.330%	1.877%

Discussion

This chapter highlights how different platforms produce systematically different amounts of policy language as predicted by their features and affordances. These results align with what the PACT tells us, that audiences matter for where politicians talk about policy and where they do not. I find that policy language is most present in *broad* audience platforms, such as debates and television. Conversely, *narrow* audience platforms have less policy language. Moreover, we see similar results when we use different policy dictionaries, look at other elected offices, and check for differences by candidate and by words. Further, when I look at the relationship between policy and sentiment, I find that policy language is associated with decreases in sentiment. That is to say, content is *more* negative when politicians are discussing policy than when they are not. This holds true for all platforms with the exception of television, which becomes more positive with policy language.

This matters greatly for thinking about how citizens are able to learn about campaigns and hold governments and candidates accountable. With a sufficient number of cues about policy and spending, voters are able to respond to changes in policy to reelect or vote out politicians. Without those cues, it is hard for voters to know where policy stands and how to respond to electoral claims. Given the results above, there are concerning indications that *narrow* audience platforms do not provide as many cues about policy. When combined with the results from sentiment, it may be the case that broad platforms encourage the kind of information sharing that is most critical to accountable democratic governance. As audience demographics and preferences change, this is a crucially important finding which can help shape future research on voters and their political life.

Some of the differences in policy volume appear to be relatively small. Does it matter that there is a 1-point difference in the percent of policy words on television versus policy words in Facebook? While the magnitude is small, consider the size of the corpus. If Facebook had the same percentage of policy words as television ads did, there would be 19,457 more policy words. This means that there is more than one policy related word in every two posts. Consider, alternatively, the difference at the level of individual posts: in 100 words, roughly three sentences, television content has one more policy word than Facebook content. *Every three sentences.* This is a considerable difference in policy content and could fundamentally alter the perceptions of the campaign as being a substantive, policy-based election.

Policy language is important, not only from a democratic standpoint, but also for candidates to help shape perceptions of them and the narrative of the campaign. By showing systematic differences across platforms, the PACT is able to provide a useful tool for researchers to understand how and where we might expect policy language to be most present and use those findings to guide future research into behavioral, cognitive, and physiological work.

Chapter 7 Political Imagery

Pictures have the capacity to become enduring symbols of moments in history. During the 2008 election, a stylized poster of Barack Obama became an iconic image of the campaign, known as "The Hope Poster" (Figure 7-1). The poster was a powerful cue of Obama's central message and theme of his campaign; and after Obama's terms were over, this image has stood as a symbol of the campaign and has adorned t-shirts, coffee mugs, and has even been co-opted by a variety of celebrities, politicians, and companies for their own pictures and logos. The Hope Poster joins a long list of important political images throughout history and highlights the importance of images in political communication.

Figure 7-1: The Hope Poster

Thus far, this project has looked at campaign communication from the perspective of text and spoken words. Yet, from campaign flyers, to newspapers, to political cartoons, the use of political imagery also has a long and interesting history (see Schill, 2012 for a review). Images convey a wide range of information, from humorous to deeply serious. Perhaps even more importantly, though, is the growth of imagery as a means of communicating with the electorate. While television advertising has been around for quite some time, the newfound importance of platforms like Facebook, YouTube, and Instagram has given voters unprecedented access to political imagery. During the 1950's, if a citizen wanted to see a picture or video of a candidate, they were functionally limited to a newspaper image, nightly news broadcasts and commercials, or perhaps a flyer mailed to them. Compare that to the 2016 campaign, where images and videos of the candidates were not only in the aforementioned platforms of the 1950's, but also on Twitter, Facebook, Instagram, YouTube, SnapChat, and website ads. This is to say nothing of the 24/7 news media and content created by non-candidate actors.

That access is noteworthy given the ease with which individuals take in information from pictures and videos over text. Consider one of the notable images from 2020, where Nancy Pelosi ripped up a paper copy of Donald Trump's State of the Union address while standing behind him (Figure 7-2). That image was quickly shared and circulated across numerous communication platforms, such as television, Instagram, and Twitter. A visual that might have been missed or not widely distributed in the 1950's is now made readily available for consumption across a wide range of platforms, almost instantly. In addition, that image can become part of political advertisements, attack ads, and candidate editorialization of the meaning of her actions. In the current media environment, the ease of access to this image, and many other political visuals, makes understanding the role and deployment of political images vitally important.

Further, both of these images provide cues about the state of politics as well as fairly clear positive and negative sentiment. However, they are also representative of content that my methods thus far would have missed. These are important pieces in the political communication ecosystem and are necessary to analyze, not only for their relevance to political campaigns but also as of test of whether the predictions made by PACT extend to the non-textual domain.

Figure 7-2: Pelosi State of the Union

I want to explore how politicians use imagery in their communications.[9] Specifically, I want to look at the relationship between platform, sentiment, and policy. I revisit findings from the preceding sections to examine whether similar trends play out in the visual space. As noted,

[9] I use image, images, and imagery to describe both picture and video content.

above, this is vital as images will contain a variety of cues and content that dictionary processing inherently misses, such as music, facial expressions, and subtle policy cues. These analyses are the final crucial step in the development of the Platform Audience and Channel Theory. This chapter begins by looking at how visual communication is deployed with respect to the audience and channel of each platform. I then outline the various ways in which images play a role in campaigns and how candidates use images. I use these literatures to build a set of expectations about sentiment and policy across two different platforms and present confirmatory results using a human coding instrument.

The Role of Images in Elections

Images have been a vital part of the American political environment since the founding of the country. I use this section to understand the role of images in political campaigning. I consider three different literatures on the importance of images above and beyond text. The first is how images convey nonverbal cues, such as symbolic imagery, music, and group photos. Related to nonverbal cues are candidate trait cues, or things like appearance and race. Finally, I look at the various ways that images can present explicit heuristic political cues, such as graphics, endorsements, and acclaims.

For my purposes, nonverbal cues in the political context is content that is not spoken but has been demonstrated to effect political outcomes. The nonverbal cues that I look at here are not necessarily explicitly political or policy related (Dumitrescu, 2016). For example, symbolic imagery such as flags has been linked to activating symbolic attitudes (Kalmoe & Gross, 2016; Dumitrescu & Popa, 2016). While flags are certainly political, showing a flag does not necessarily translate to an explicit cue or signal. There is also evidence that the demographics of the individuals that candidates choose to be photographed with matters. Sulkin and Swigger find that candidates who represent themselves with various groups (such as military, children, and blue-collar workers) were more likely to take legislative actions for that group, like introducing or co-sponsoring bills (2008). These cues can be used by voters to make assumptions about the type of politician that candidate will be and the types of policies they will pursue.

The nature of nonverbal cues is that they can co-occur with explicit political content. Visual communication can include emotion evoking cues, such as music, lighting, and visual cues (Sabato, 1981; Thorson et al., 1991). Emotion evoking music when combined with emotion evoking words is a powerful combination of messaging that cannot be easily duplicated in a primarily text-based platform. Brader finds that the addition of music can "dramatically influence responses to campaign ads" (2006, pg. 389). Thus, the importance of co-occurring messages (nonverbal cues alongside other information) can substantially change the effects of message exposure.

Related to nonverbal cues are what I am terming 'candidate cues.' These are very much associated with the literature on nonverbal cues, but I want to highlight what I consider to be important differences between nonverbal cues and candidate cues. Candidate cues are the signals that voters use based on the candidate's appearance, physical characteristics, speaking voice, or demeanor. For instance, there is a great deal of work on how candidate appearances affect evaluations of them. Attractive candidates have been demonstrated to have an electoral advantage (Ahler et al., 2017) and primary candidate ballot photos are used by voters as cues in low-information environments (Banducci et al., 2008; Carpinella & Johnson, 2016). Facial features can also prime ethnic considerations (Moehler & Conroy-Krutz, 2016). There is also evidence that both men and women prefer candidates with lower-pitched voices, as well (Klofstad et al., 2012). These are even beyond the body language of the candidates, which is not inconsequential as we have seen both from the anecdote about Nixon and Kennedy at the very beginning of this project, but also during other elections (Streeck, 2008; Patterson et al., 1992).

Another body of literature is focused on the ways in which visual imagery is can be an effective way of transmitting more explicit heuristic cues to voters. These are not the nonverbal cues I described above, but deliberately political cues and communications. Voters use cues to make evaluations of politics and politicians (Lupia & McCubbins, 1998) and there are a wide range of cues that are important to voters, such as party identification and endorsements (Arceneaux & Kolondy, 2009; Dancey & Sheagley, 2013). The content of these cues may not actually differ from what a voter would have access to from reading a tweet or a press release, but visual communication makes access to these cues easier. Consider a campaign that posts a picture on Instagram listing all of the organizations and prominent individuals who endorse them. That graphic conveys a great deal of information quickly and succinctly. It does not require much effort on the part of the viewer to see that Candidate A has a 100% pro-NRA voting record or that Planned Parenthood endorsed Candidate B. Those are powerful signals to voters that can quickly and easily digest. This may be significant, then, as cues are notably important for voters who are not normally interested in politics (McDermott, 1997; Banducci et al., 2008).

The point that I intend for this section to make is that imagery is functionally similar to other forms of communication for my purposes; that it has the capacity to convey information that voters can act upon and that there may be quantifiable differences in the content across platforms. Further, images may also make the digestion of information easier. Images can spread far more information than text can as images are processed faster and the information is retained longer than textual information is (Boomgaarden et al., 2016). That means that even if a person does not see the entire image or spend a lot of time looking at it, because images are processed "holistically," they may still receive the message and process the information (Nagel et al., 2012). This may be even more important as information in images may be much easier for citizens to be incidentally exposed to content that comes in image form rather than text (McQuarrie & Mick, 2003). As more users find themselves on social media sites, which are all classified as *narrow* platforms in the PACT, there is potential for exposure to systematically different information, not just for the reasons noted in previous chapters but because of the prevalence of images.

In sum, depending on how candidates use images, there may be differential effects across platforms, especially for low-attention or low-interest voters who use those platforms but do not purposefully engage in political information seeking but are exposed to images through their platform of choice.

How Candidates Use Images

There is a rich literature describing how candidates use images; with some of the more prominent approaches being (a) videostyle, (b) Functional Theory analysis, and (c) the visual framing framework (Kaid & Johnston 2001; Benoit, 1999; Grabe & Bucy, 2009). These are certainly not the only ways in which visual campaigning and imagery have been analyzed, but they are useful in that they have been used for a number of years and across different platforms. I consider each in turn, below.

The developers of videostyle, for instance, suggest that television, the primary method of image communication at the time of writing, has its own "language" and that candidates must match this language, through their own personal approach, in order to communicate (Kaid & Johnston, 2001, pg. 26). They do this through a combination of verbal, nonverbal, and production techniques (Kaid & Davidson, 1986). Videostyle is built on the concept of impression management by Goffman (1978) and tells us is that visual communications is a complex dynamic of goals of the campaigner and expectations of the platform they are using and the audience. Work using videostyle has highlighted how candidates are aware of the ways in which visuals are interpreted and are deliberate in their usage and approaches. In so doing, candidates are attempting to tailor their approaches based on the platform that they are using.

Functional Theory analysis evaluates political campaign content for acclaims, attacks, and defenses (Benoit, 1999). This approach is not solely applicable to image content as it has been used on debates and speeches (Benoit & Brazeal, 2002). Functional Theory analysis is useful as a tool to think about how candidates portray themselves in visual-centered platforms, however, as it speaks to the role that various message strategies play in campaign communication. Results have highlighted how there are differences in acclaims, attacks, and defenses across platforms. For instance, Benoit finds that campaign posters, a platform that relies on visual communication, are more likely to contain acclaims than attacks or defenses (2019). His argument is that the inherent structure of visual platforms, in this case posters, leads to the use of acclaims over the other categories. Functional Theory analysis has highlighted the relevance of the ways that platform structure matters, especially for visual communication platforms.

Finally, Grabe and Bucy look at the ways in which candidates attempt to market themselves to voters (2009). They identify three different meta-frames that a political candidate can be cast in. How a candidate is framed is a function of both their own messaging and communications as well as how media and other political actors attempt to frame the candidate. The three frames are the populist campaigner, ideal candidate, and sure loser, each of which has sub-frames that tap into traits and characteristics of politicians, such as compassionate or likeable. For instance, the authors also point out that candidates can use visuals to depict themselves engaging in populist behaviors, such as mingling with crowds or dressing casually. These archetypes are developed to "deliberately promote particular theses, symbolic meanings, and character qualities" (pg. 86). There is, of course, a tension between how a candidate attempts to portray themselves and how their opponent might try and frame them. The authors also note that there are meaningful consequences when the mental frame that voters have about the candidate does not match the frame being transmitted (2009). Candidates are in a competition, then, to control the frame that they are portrayed in.

The above literatures make clear that nonverbal cues are important and are strategically used by candidates. There is also evidence that campaigns use imagery for acclaiming, attacking, and defending, suggesting differences may inherently exist based on the goal of the communication. Finally, campaigns are cognizant of their image, and pay attention to how they come across through visual depictions of themselves. The point is that images may be used differently across platforms. As images become more prevalent in the media ecosystem and the ease of access to images increases, understanding how campaigns utilize images is crucial to understanding political campaign communications. I next consider whether images vary in the ways that the PACT has shown textual information varies.

Expectations

There are clear connections between previous work on images and how the PACT anticipates differences in content across platforms. Before I turn to platform specific expectations, however, I want to outline why there will be differences across platforms in general. Just like with text, the transmission of visual communications is dictated by the technical features and user affordances of the platform. For example, Instagram allows photo and video uploads, but requires the use of the app instead of a website. This feature constrains the types of images that users can upload, and generally forces them to use their mobile device's camera. That means that the technical features of Instagram differ from Facebook, which allows users to upload from internet connected devices, such as laptops. These platforms' affordances are also going to differ as a result of these feature constraints. The modal picture on Instagram may be more casual and personalized than Facebook because expectations about the kinds of pictures on each platform are different; and this is rooted in part in the use of mobile versus other cameras, of course.

As the features and affordances constrain the visual content that politicians can put on platforms, they will make strategic decisions about the images they communicate to voters based on the audiences and channel of each platform. This is the same dynamic for images as it was for text. Consequently, I expect that visual content on *broad* audience platforms will be more negative and contain more policy language. The nature of the audience is important because, as highlighted in Chapter 5, campaigns can use negativity strategically with *broad* audiences to drive behavioral, evaluative, and cognitive changes in those exposed to messaging. Thus, imagery used during television advertising, which is a *broad* audience platform that allows for the transmission of images and videos, will be more negative and be more policy focused than *narrow* platforms.

Candidates using television to communicate will take advantage of the use of nonverbal cues in their advertisements, as outlined above. The presence of music, negative imagery, and ominous voiceovers are all common staples of television advertising. In part, audiences expect those types of messages, even as they complain about the tone of political campaigning. While other platforms certainly can and do use similar production techniques, the structure of television means that there is a captive audience for the entirety of an advertisement whereas it is far easier to ignore or scroll past an advertisement on a social media site. Of course, users of television can mute or change the channel, but there are costs to doing so. There are incentives, then, to develop advertisements that can elicit the emotional reactions that a campaign is looking for while exposing that message to the largest possible audience.

Further, I would expect that television will use more policy language. One reason is that policy language and cues can quickly be distilled down into easily digestible messages using images as opposed to spoken word (Edwards, 2012). As noted above, images are easily understood and retained compared to text. However, in order for that to reach voters, they must be at least somewhat attentive. It is not immediately clear that is the case with *narrow* platform users, where users often report that they are incidentally exposed to content (Gil de Zúñiga et al., 2017; Weeks et al., 2017). In order to understand this, we must think about the nature of consumption on *narrow* platforms compared to *broad* ones. A *narrow* platform is often made-up of social connections sharing information with one another. Because individuals self-select into who they are exposed to, the messages are generally of personal interest to the user. When a campaign is messaging on a *narrow* platform, they are competing with the user's social ties for attention. Long messages with a lot of policy mentions may not be ideally suited for this venue as opposed to messages of inclusion and positivity. So, while policy language may be relevant to all citizens across all platforms, there are other types of content, such as personalized looks into the candidates life and positive messages about the in-group, that might resonate more on *narrow* platforms, much of which is described in Chapter 6.

Images that are communicated on *narrow* audience platforms, such as Instagram, ought to be more positive and, on average, contain fewer policy mentions. Past work already points in this direction. Muñoz and Towner, for instance, found that candidate photos on Instagram were heavily focused on large audiences, symbolic imagery, and campaign paraphernalia (2017). Relatedly, Nashmi & Painter found that there was a strong degree of similarity among the 2016 presidential candidates in their use of SnapChat, with the exception of Hillary Clinton (2018). In fact, those finding align with O'Connell, who found that female members of Congress interacted with their Instagram platform differently than their male counterparts (2018). These results suggest that there is a strong degree of homogeneity in platform usage, but also that political actors are conscious of *how* they come across and attempt to fit their approach to the platform expectations. It is noteworthy, then, that none of these papers found high degrees of policy specificity or negativity in communications on *narrow* platforms. Thus, given the nature of visual communication as described above, I would expect that:

H1: Broad audience platforms (television ads) will be, on average, more negative than narrow audience platforms (Instagram).

H2: Broad audience platforms (television ads) will have, on average, more policy mentions than narrow audience platforms (Instagram).

I now turn to an explanation of how I collect human coded data for the visual dataset and then turn to results.

Capturing Differences in Visual Campaigning

This chapter uses the television advertising database and the Instagram image database, as described in the data chapter. Dictionary processing that I used in previous chapters is not useful here, so instead I turn to human coders. I use 2,750 crowd-sourced human coders from

Amazon’s Mechanical Turk platform and developed a survey with embedded images and videos for coding of tone and policy. It is important to note here that while the predictions that I am making above are similar to those made in Chapters 5 and 6, the methods used are significantly different, as are the objects of analysis. This chapter focuses on data in which humans code the entirety of content, not just the text. The survey described below provides related but fundamentally different data from what has been analyzed in previous chapters.

To start, each worker was informed that the purpose of the survey was to evaluate images and videos for their tone and policy presence. They were asked to not consider their own ideology or partisan affiliations as much as possible while they were evaluating the content. The instructions provided were as follows:

> *“You will be asked about the **tone** of each item, or how positive or negative that item is. You will be asked if the item contains mentions of **policy**. By policy, we mean things like Medicaid, international relations, Universal Basic Income, or immigration. We do **NOT** mean campaign messages such as "Vote for Candidate X" or "Candidate X can win".*
>
> *We do **NOT** want you to consider the item from your own ideology. For example, if you see a picture of Hillary Clinton and you are a Republican, that does not make the picture negative. We are interested in if the intent of the item was positive or negative.*
>
> *This survey will ask you about a series of campaign images and videos from previous political elections. We want to know how you view the image. It is important that you do not consider your personal political ideology, affiliations,*

or leanings. We are interested in what the candidate was trying to communicate through these visuals."

Respondents were then shown a picture and asked to evaluate the tone of the image and if there are any mentions of policies in the picture. The question wording with response options being negative, positive, or neutral are:

> "Regardless of your personal political beliefs, how would you rate the overall TONE of the image?"

For policy, the question is:

> "Regardless of your personal political beliefs, does this image contain any mentions of POLICIES?"

Response options are yes or no. They then repeated this task for another image. The sentiment question is coded -1, 0, and 1 whereas the policy question is a binary with 1 equaling yes.

These first two images are the same for each respondent and are used to ensure that they are correctly following instructions. The images in Figure 7-3 must be rated as "negative" and "yes" for tone and policy presence for image A and "positive" or "neutral" and "no" for image B. Respondents who selected different options were informed that they had not successfully completed the calibration exercise and were removed from the survey. For those who were able to correctly identify each photo, they then saw a series of 5 pictures from the Instagram dataset. For each picture, they answered the tone and the policy question. They were then shown one television advertisement and answered the same tone and policy questions.

Figure 7-3: Calibration Images

Embedded in the survey is a random draw of 5 pictures and a video. These are drawn from the sample (described in Chapter 4) of Instagram posts and television advertisements, totaling 4,482 and 1,305 respectively. In total, each subject saw 7 pictures (two as calibration pictures) and 1 video. In total there are 13,750 picture codes and 2,750 video codes. Not all of the videos and images ended up getting coded due to the random assignment of respondents, and the removal of respondents during the calibration test.[10] That said, the coded dataset includes 4,269 pictures and 1,135 videos.

Following coding, worker answered basic demographic questions on gender, age, race, education, employment status, interest in politics, party id, and ideology. I include breakdowns of each of these questions along with their full text in the Appendix, but briefly: 59.16% of the sample is male; 40.8% is between the ages of 25 and 34; 64.63% is white; 70.94% has at least a 4-year degree; 65.38% is employed full-time; 55.78% is at least “very interested” in politics; 40.36% identifies as a Democrat; 23.35% as Republican; 40.83% rated themselves as “liberal” or “extremely liberal”; and 14.69% as “conservative” or “extremely conservative”. The

[10] About 60% of the respondents failed at least one of the calibration tests. The survey instrument assigns photos and videos when the survey starts, not when the respondent passes the calibration tests. Thus, those missing images and videos are a result of being assigned to individuals who failed the tests but did not get reassigned to others before the quota of respondents was met.

demographics of the coders leans white, Democratic, and educated compared to the U.S. population as a whole. However, given the instructions and calibration tests, partisan biases should be minimized. (I also test for this later.) I now turn to the results of this coding instrument.

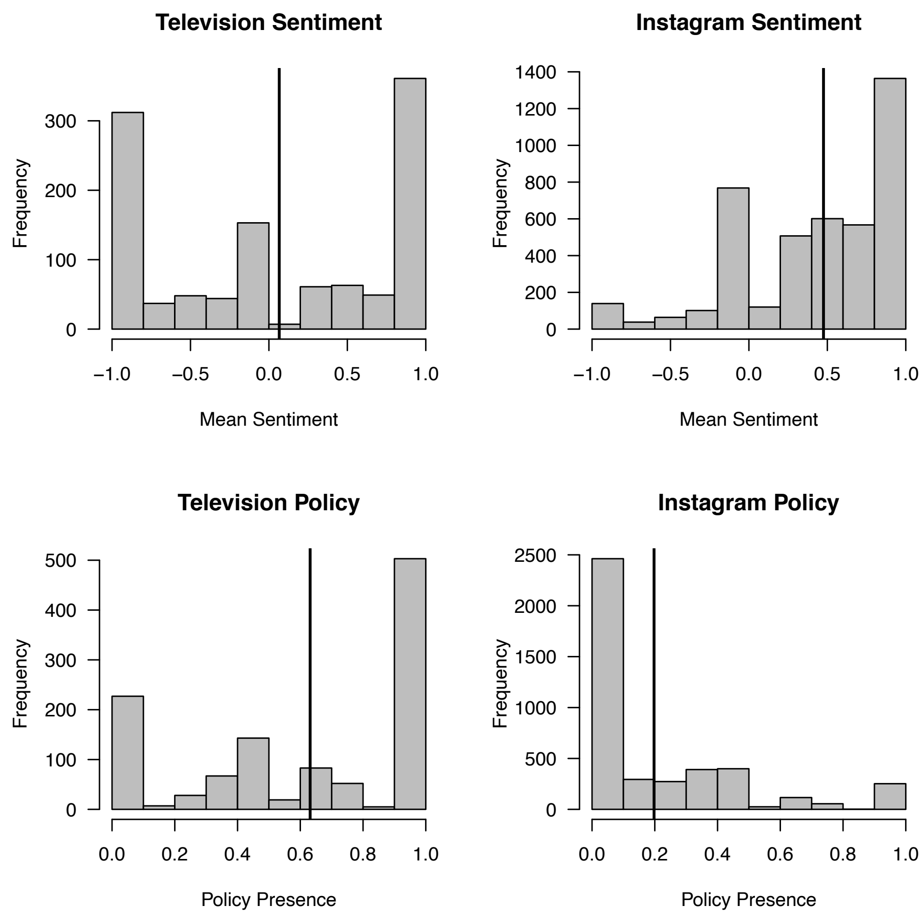
Results

The first results that I look at are those for sentiment for both the pictures and video codes. I calculate sentiment as follows: each image and video is coded -1, 0, or 1 for responses of "negative", "neutral", or "positive", respectively. I then take the average of each items codes and assign that to the item. For instance, a picture with 3 coders who rated it "negative", "negative", and "neutral" would equate to -1, -1, and 0 with an overall sentiment score of -0.667. Finally, I take the average of all of the images or videos for the platform to come up with the platform mean. I use the same strategy for policy, except with "no" and "yes" being coded as 0 and 1, respectively. I present the results for both sentiment and policy scores in Figure 7-4 with black lines indicating the mean for that platform and measure.

Mean sentiment for television advertisements is 0.066 (SD = 0.812). For Instagram pictures, it is 0.475 (SD = 0.500). That means that Instagram pictures are rated significantly ($p < 0.001$) more positive than television ads are. When we look at the allocation of assigned scores, we see that, for television, there is a clear bimodal distribution with many of the videos being rated either completely negative or completely positive.[11]

[11] I did also look at sentiment scores excluding pictures and videos that had only one coder. That means 692 images were excluded and 346 videos. Doing so did not fundamentally change the results, so I use the entire coding set here.

Figure 7-4: Imagery Sentiment and Policy Scores



For Instagram, however, few of the pictures are rated as completely negative with most being completely positive or between neutral and positive. Not only are the mean scores different, but the experience of consuming these platforms is different. Television is a fairly mixed bag, with about half of the ads being negative and about half being positive. On Instagram, however, the *narrow* audience is being exposed to almost entirely positive messaging.

Policy codes are also confirmatory of the expectations of the PACT. We see that only a small number of Instagram pictures are rated as having policy with mean of 19.76% (SD = 28.72). For television, the results show that 63.14% of ads are rated as having at least one mention of policy (SD = 39.16%). This aligns with H2, that the *broad* audience platform contains more policy references than the *narrow* one does. We do see a similar distribution for television policy codes as we do for sentiment that is to say, a bimodal distribution. The same applies for Instagram, its distribution is similar to the one for sentiment, although reversed with only a few pictures discussing any policy.

Television viewers would on average be exposed to a relatively negative set of advertisements which include policy language. Users of Instagram, conversely, would be exposed to a relatively positive set of images that do not contain much policy discussion. This is, of course, concerning from a democratic standpoint as I have outlined the previously. If users are being systematically exposed to different information, then there are reasons to suspect that there may be differential political outcomes depending on which platform citizens use.

I also consider the relationship between sentiment and policy, as I did in Chapter 6. I do this by looking at the mean sentiment scores when the policy score is greater than 0.5 and less than 0.5. This will functionally give me the sentiment scores when more than half of coders rated the item as containing policy and less than half did. For television, mean sentiment when policy is greater than 0.5 is 0.127 (SD = 0.802) and when policy is less than 0.5 it is -0.028 (SD = 0.846). Television is more negative when there is less policy than it is when there is policy. This aligns with findings from Chapter 6. Conversely, Instagram sentiment is 0.508 (SD = 0.459) and 0.263 (SD = 0.699) when policy is less than and greater than 0.5 respectively. These findings are the opposite of television, Instagram sentiment is lower when policy language is used than when it is not. This, again, aligns with other *narrow* audience platform findings.

I now turn to some additional tests of these findings.

Robustness Check

Even with confirmatory results for both H1 and H2, I want to look at a few different approaches to ensure the robustness of my findings by considering whether the demographics of workers influences their scoring and regard this as a test of the validity of the sentiment coding of images and videos.

Demographic Tests

I start my exploration into the demographics of the respondents by first comparing the means of sentiment by party ID. I do this by collapsing the 7-point party ID question into either Democrats or Republicans. I then look at the mean sentiment for each video based on if the respondent is coded as a Democrat or a Republican. There is a no statistically significant difference in tone coding, with democrats rating videos at 0.053 and Republicans rating them at 0.079 (SD = 0.877 and SD = 0.896, respectively; $p=0.583$).

I also look at tone when partisans are rating the out-party. For Democratic coders rating Republican candidates, tone is more positive than when they are rating Democratic candidates (0.064 vs. -0.05). The same relationship exists for Republican coders rating Democratic candidates and Republican candidates. Those vying for the GOP nomination are rated as being more positive by their co-partisan coders than the Democratic candidates are (0.079 vs. -0.036). This aligns with the relationship that I found using dictionaries, which gives sentiment scores of 1.485 for Democrats and 1.610 for Republicans, indicating that the Republicans were more positive in their advertising. This again suggests that the coder results are not affected by partisanship.

I do find significant differences for male versus female coders for sentiment, however. Women rated video advertisements more negatively than men did with a mean sentiment score of -0.005 (SD = 0.889) compared to 0.082 for men (SD = 0.854). These differences are marginally significant ($p = 0.045$). There are no differences between their ratings for policy presence in videos ($p = 0.155$). For Instagram posts, conversely, there are no significant differences in sentiment ratings for men versus women ($p = 0.248$) but there are for policy language, with women rating images lower for their policy content at 18.13% compared to 21.36% (SD = 34.00% vs. SD = 33.28%; $p < 0.001$). That being said, an investigation into gendered reactions to content is worthwhile for future work.

Discussion

The importance of visual communication cannot be overstated. Imagery has increasingly become the modal way that citizens take in political information, and the growth of *narrow* audience platforms has allowed users to see into parts of candidate lives that were previously closed off. Further, it has allowed greater access to political information in general. Yet this chapter has highlighted how that information is not distributed equally across platforms, with *broad* audience platforms, such as television advertising, being both more negative and containing more policy language than the *narrow* audience platform of Instagram.

This matters a great deal as we know that images are better at communicating information to citizens than text is. Given the results, we could imagine a voter who primarily watches television and is more informed and more likely to vote or donate money than a user of Instagram due to the nature of the content on television. That content is, in part, determined by the audience of the platform, which inclines candidates to use more negative words, nonverbal cues, and production techniques in their advertising. Instagram, however, is more positive and contains fewer policy mentions. This may be due to candidates focusing more on their personal lives, their supporters, and their campaign events than negative attack ads or policy discussion.

One interesting note for the coding project is that while I had 2,750 coders, it took 6,868 attempts by coders to get to that number. That means that 59.96% of potential coders failed at least one of the calibration coding tests before they were shown the actual coding task. Of course, some of those failures can be attributed to bots and individuals not paying attention. However, there are undoubtedly individuals who genuinely have disagreements about the tone and substance of those images and that those disagreements are not necessarily driven by partisan motivations. Instead it could be the case that the images, to some people, were genuinely viewed as being positive instead of negative or about policy instead of not. While I endeavored to select pictures with clear-cut answers to those questions, I believe that the number of people failing these tasks may speak to the degree to which picture coding is a fuzzy method at best. For scholarship that seeks to use complex coding and assignment algorithms with machine learning and adversarial networks, these results suggest the complex nature of pictures means using computational approaches must be done carefully and with a great deal of testing.

Much like the findings in Chapters 5 and 6, the visual corpus that I evaluate sheds much needed light on the ways that content differs across platforms. The PACT argues that the degree of homogeneity in the audience is a crucial factor in predicting what kinds of content that audiences are exposed to; with results confirming that expectation. When we consider the role that platforms play in a democratic system, these differences in content may be highly consequential. We know that candidates are using platforms strategically and are cognizant to matching content to the audience that they are communicating to. We also know that they use nonverbal cues and production techniques to send signals to voters. Because images and video are better at sharing information with users, these cues and signals may have a greater chance of becoming part of the political evaluations and calculations that voters make. The end result of these findings may be a media environment where television users are more informed and more politically activated than users of other platforms, which could have serious consequences for the trajectory of voting, polarization, and government accountability.

Chapter 8 Conclusion

This project began with the question "does a political campaign look the same across different platforms?" I argue that, because platforms are not the same, we ought to expect variations in content. I conceptualize communication platforms as being comprised of different technical features and user affordances. These shape the content that is communicated on each platform.

The Platform Audience and Channel Theory is my approach to understanding variations in content by platform. It argues that the audience and channel of a communication platform are consequential to the type and substance of content that political campaigns communicate. Audience is relevant for the degree to which it is ideologically homogenous, i.e., how *broad* or *narrow* the audience is. Channel describes the capacity of the platform to allow for interactions between candidates. Platforms which enable easy communication between candidates, such as a debate, are classified as *shared* channels whereas platforms relatively free of opponent interactions, such as speeches given at a rally, are *independent* channel platforms. This framework leads me to predict that there will be systematic differences across platforms depending on their audience and channel.

I find that *broad* audience platforms with *independent* channels are more negative than *narrow* audience and *shared* channel platforms. This means that platforms such as television advertising are relatively more negative than Facebook, Twitter, or political speeches. Further, the substance of content on platforms differs, where *broad* audience platforms like television advertisements and debates contain more policy language than *narrow* platforms like speeches, Facebook, and Twitter. These content differences do not apply only to text: I look at visual communication on Instagram and television and find that television advertisements are more negative and contain more policy language than Instagram does, in line with the results for text and with the predictions made by the PACT.

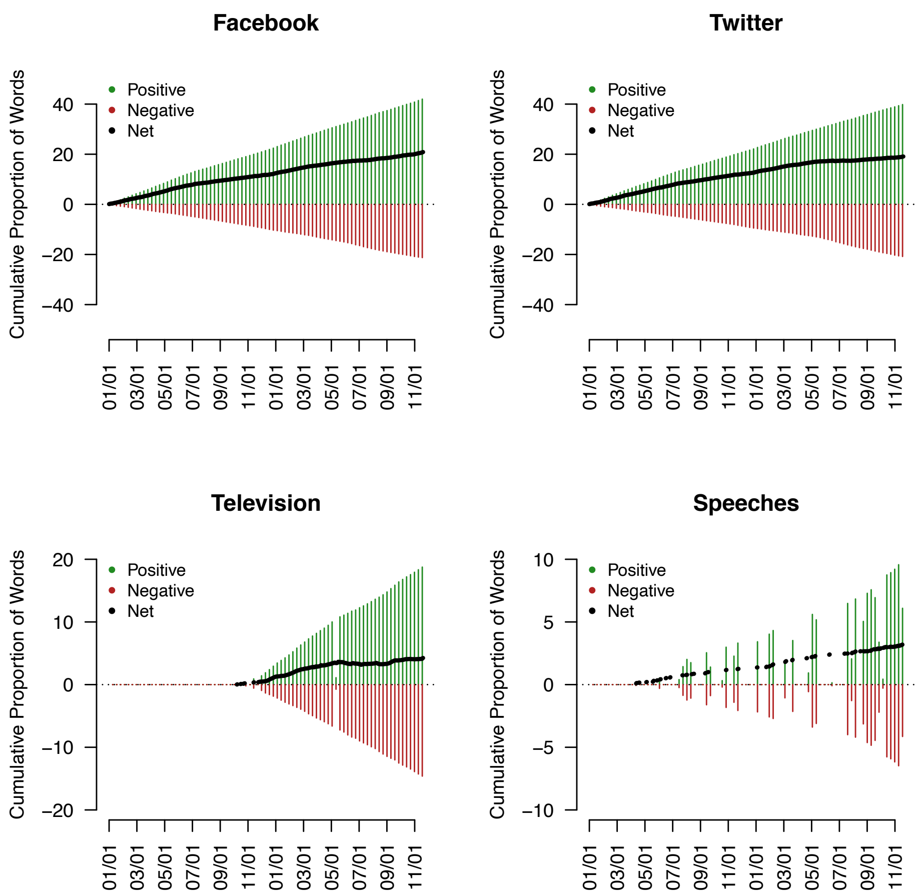
These differences may have significant effects on citizens. We know that negative content is more likely to draw the attention of viewers, change evaluations, and drive behaviors like voting and that there is evidence that positive content can drive engagement with content, especially for online platforms (Ansolabehere et al., 1994; Ansolabehere & Iyengar 1997; Lau & Sigelman, 2000; Gerodimos & Justinussen, 2015; Housholder & LaMarre, 2015; Soroka et al., 2019). We also know that policy cues can be used by citizens to form evaluations of candidates, update information on the state of policy, and serves a vital democratic function of holding governments accountable (Wlezien & Erickson, 2002; Arceneaux, 2006; Trammell 2006; Blais & Perrella 2008; Boydstun et al., 2013; Hiaeshutter-Rice et al., 2019). Functionally speaking, the presence of negative or positive sentiment and policy language in communications can significantly alter political outcomes for those who are exposed.

Just how different does a campaign look on one platform or another. Consider the sentiment of a campaign, as experience by users of different platforms. Figure 8-1 shows the cumulative proportion of words in each corpus that is positive (green bars), negative (red bars) and the net sentiment over time for Facebook, Twitter, television ads, and speeches.[12] I use proportion to control for the size of each corpus and cumulative to evaluate what exposure on that platform might look like if a user saw everything in my data. As we can see, both Facebook and Twitter have more *overall* sentiment as indicated by the large y-axes. Further, they have

[12] I omit debates (as all observations are on single days) and Instagram (due to the different coding scheme used).

more *positive* words, as indicated by the fact that the green bars, indicating cumulative proportion of words that are positive, are larger than the red bars. Television, conversely, has a much more even distribution of positive and negative words, although the overall tone is positive. I should note here that gaps in the x-axis, both before the lines start and in the middle, are dates where there is no data. Speeches are more positive than negative, although there is less *overall* sentiment (again, scale of the y-axis indicates as much).

Figure 8-1: Cumulative Tone By Platform



I consider these findings to be rather stark. Users of Facebook and Twitter are being systematically exposed to significantly more positive content over the course of the election than other platforms, with television ads being the least positive of the group. I present this image as final illustration of the ways in which campaign content varies across platforms – the central argument behind the PACT.

The principle implication of my findings is that *the experience of a political campaign can substantively and significantly differ for individual citizens depending on which communication platform citizens are getting political information from*. This means that different subsets of the population may have differential political behaviors, attitudes, and evaluations depending on which platforms they use. As there is increasing evidence that there are demographic differences in the audiences of platforms, these implications take on an even more pressing meaning as different age-groups and political leanings are being exposed to differential content.

As I stated earlier in this piece, this work is, at least in part, a response to other scholarship which has argued the media ecosystem is functionally the same regardless of which platforms content is consumed by (Chadwick, 2017). I view the PACT as a gentle pushback against that line of thinking insofar as political campaigns are concerned. The hybrid media system is one in which different platforms work in concert with one another, with various actors and stakeholders pushing towards a common goal. That may in fact be the case but arguing for similarity across platforms misses the fact that platforms are fundamentally different from one another, with consequently different content. I do not necessarily see the hybrid media system and the Platform Audience and Channel Theory as being in conflict. However, I contend that the hybrid media system misses important differences in content and, subsequently, misses potentially serious differences in what citizens are exposed to. Indeed, I show empirical evidence here that political campaigns do not operate in the way that the hybrid system would predict.

Consequently, it is my contention that the PACT offers vital insights that are relevant to a wide range of research fields. I perceive its value, of course beyond what it adds to human knowledge, as twofold. The first is that it provides direct insights into how to think about content across platforms. This is invaluable for scholars who seek to understand the role that communication platforms play in society, even if their work does not explicitly say they are studying platforms or platform variations, such as work on exposure to political information (e.g. Bartels, 1993; Garrett et al., 2013; Garrett et al., 2014), political learning (e.g. Leshner & McKean, 1997; Holbrook, 1999; Bode, 2016; Moeller & de Vreese, 2019), and the effects of media exposure on political behaviors (e.g. Scheufele, 2002; Gerber et al., 2009; Namkoong et al., 2012). This is especially important as much of that work relies tools such as experimental stimuli or survey questions. Instruments that are built using the PACT as a guiding principle are more likely to mirror reality and, thus, increasing the external validity of the findings. The effects of political content exposure is an increasingly important field of study and better tools makes for better research.

The second is that the PACT is an important theoretical advancement in the study of political communication. Perhaps the most important intervention it makes is to alter our understanding of political information exposure. Exposure, whether intentional (Kitchens et al., 2003; Valentino et al., 2008; Himelboim et al., 2013) or incidental (Tewksbury et al., 2001; Weeks et al., 2017; Beam et al., 2018), is a necessary precursor to a number of important areas of study, including political knowledge, polarization, and political behavior. If, as I argue here, content varies across platforms, then scholarship must take seriously platform differences and integrate an understanding of audiences and channel into studies of political information and communication. Indeed, some of the most topical areas of research at the time of this writing focus on content communicated through various platforms and the effects of that content. The PACT is relevant to many of these areas of study. For instance, the PACT can speak to where misinformation may be more likely to appear (Ratkiewicz et al., 2011; Guess et al., 2020). It can also shed insights into racially divisive language, group language, as well as political topics of interest, such as science communication (Huber & Lapinski, 2008; Budesheim et al., 1996; Schäfer, 2012).

Further, while the PACT is focused on political campaigns, the underlying arguments about affordances and features ought to have explanatory value for other users of communication platforms, such as news organizations. Answering questions about the content of *The New York Times* website compared to its social media posts or the actual hard copy of the newspaper, for instance, is an important question as well as one that is open to integrating technical features and user affordances. It is my hope that the Platform Audience and Channel Theory can encourage researchers to take into consideration how these two vitally important structures of communication platforms.

This project has offered straightforward empirical tests of how the content of platforms varies. Of course, I do not test all or even most ways in which content may differ, even though there are a large number of other predictors of content variation that have been look at in scholarship. Some of those predictors may be antecedents of platform structure but interact in systematically different ways. For example, the race or gender of candidates could alter how they communicate across platforms. There also is a wide range of content that has political implications which I do not test look at here, such as group language, racial issues, or spending language. These are also important considerations and understanding where they are used (or not) is a worthwhile pursuit. The PACT provides a framework for making testable predictions about these important messages.

Testing every possible permutation of content predicated by audience and channel was never the objective of this project, of course. Instead, what I aimed to accomplish was a first set of empirical tests of some aspects of the argument that campaign content varies, at least in part, by audiences and channel. Moving forward, one of the contributions that the PACT makes to scholarship is the ability to set expectations for content on future platforms. The PACT is not linked to current platforms; it allows researchers to develop expectations about the kind of content they should expect on as-yet-undeveloped or understudied platforms. For instance, what might we expect TikTok political campaigning content to look like? Or would we expect virtual reality-based advertising to be more negative than Twitter? These are questions that the PACT can provide guidance on.

This is not to say platform specific theory is useless, far from it. Platform centered theory can shed valuable light on the intricacies of how platforms are used, how users engage with content, and the effects that exposure to content on that platform has on users. Indeed, much of what I build on for the PACT comes from platform specific theory. However, the major failings of these models is that they are so specific that we cannot use them to further our understanding across other platforms and yet they are often framed in just such a way. What we know about television does not necessarily translate to Facebook, as I have empirically demonstrated here. One of my objectives, then, has been to develop an approach that researches can use when new platforms appear.

To close, I found significant and important differences in content across six different platforms in both text and visual communications. I highlighted how individuals who use one platform over others may be exposed to specific types of content which may have implications for their political life. As a result, I argue that the Platform Audience and Channel Theory provides scholars with a durable and straightforward way of analyzing content across communication platforms. It is my hope that the PACT can be used to further test variations in content as well as provide a framework for platforms that have yet to be developed.

Appendices

Appendix A: Pairwise Candidate Tukey Tests

	Difference	Lower	Upper	p adjusted
carson-bush	2.83	2.37	3.30	0.00
chafee-bush	-3.11	-4.12	-2.09	0.00
christie-bush	0.30	-0.18	0.78	0.80
clinton-bush	-0.77	-1.04	-0.49	0.00
cruz-bush	0.45	0.10	0.80	0.00
fiorina-bush	1.69	1.11	2.26	0.00
graham-bush	-0.36	-0.89	0.16	0.64
huckabee-bush	1.13	0.62	1.64	0.00
jindal-bush	0.16	-0.55	0.87	1.00
kasich-bush	1.54	1.13	1.95	0.00
omalley-bush	0.74	0.24	1.24	0.00
pataki-bush	0.67	0.01	1.34	0.04
paul-bush	1.01	0.54	1.48	0.00
perry-bush	1.62	0.88	2.36	0.00
rubio-bush	0.20	-0.11	0.51	0.75
sanders-bush	2.09	1.80	2.38	0.00
santorum-bush	3.17	2.57	3.77	0.00
trump-bush	-0.35	-0.62	-0.09	0.00
walker-bush	1.90	1.34	2.46	0.00
webb-bush	0.96	0.27	1.65	0.00
chafee-carson	-5.94	-7.00	-4.88	0.00
christie-carson	-2.53	-3.10	-1.96	0.00
clinton-carson	-3.60	-4.01	-3.19	0.00
cruz-carson	-2.38	-2.84	-1.92	0.00
fiorina-carson	-1.15	-1.80	-0.49	0.00
graham-carson	-3.20	-3.80	-2.59	0.00
huckabee-carson	-1.70	-2.29	-1.10	0.00
jindal-carson	-2.67	-3.44	-1.90	0.00
kasich-carson	-1.29	-1.80	-0.78	0.00
omalley-carson	-2.09	-2.68	-1.51	0.00

pataki-carson	-2.16	-2.89	-1.43	0.00
paul-carson	-1.82	-2.38	-1.27	0.00
perry-carson	-1.21	-2.01	-0.41	0.00
rubio-carson	-2.63	-3.06	-2.20	0.00
sanders-carson	-0.74	-1.16	-0.32	0.00
santorum-carson	0.34	-0.33	1.01	0.97
trump-carson	-3.18	-3.58	-2.78	0.00
walker-carson	-0.93	-1.57	-0.29	0.00
webb-carson	-1.87	-2.62	-1.12	0.00
christie-chafee	3.41	2.34	4.47	0.00
clinton-chafee	2.34	1.35	3.33	0.00
cruz-chafee	3.56	2.54	4.57	0.00
fiorina-chafee	4.79	3.68	5.91	0.00
graham-chafee	2.74	1.65	3.83	0.00
huckabee-chafee	4.24	3.16	5.32	0.00
jindal-chafee	3.27	2.08	4.46	0.00
kasich-chafee	4.65	3.61	5.69	0.00
omalley-chafee	3.84	2.77	4.92	0.00
pataki-chafee	3.78	2.62	4.94	0.00
paul-chafee	4.12	3.05	5.18	0.00
perry-chafee	4.73	3.52	5.94	0.00
rubio-chafee	3.31	2.31	4.31	0.00
sanders-chafee	5.19	4.20	6.19	0.00
santorum-chafee	6.27	5.15	7.40	0.00
trump-chafee	2.75	1.77	3.74	0.00
walker-chafee	5.01	3.90	6.11	0.00
webb-chafee	4.06	2.89	5.24	0.00
clinton-christie	-1.07	-1.49	-0.64	0.00
cruz-christie	0.15	-0.33	0.63	1.00
fiorina-christie	1.38	0.72	2.05	0.00
graham-christie	-0.67	-1.29	-0.04	0.02
huckabee-christie	0.83	0.23	1.44	0.00
jindal-christie	-0.14	-0.92	0.64	1.00
kasich-christie	1.24	0.72	1.77	0.00
omalley-christie	0.44	-0.16	1.04	0.52
pataki-christie	0.37	-0.37	1.11	0.97
paul-christie	0.71	0.14	1.28	0.00
perry-christie	1.32	0.51	2.13	0.00
rubio-christie	-0.10	-0.55	0.35	1.00

sanders-christie	1.79	1.35	2.22	0.00
santorum-christie	2.87	2.18	3.55	0.00
trump-christie	-0.65	-1.07	-0.23	0.00
walker-christie	1.60	0.95	2.25	0.00
webb-christie	0.66	-0.10	1.42	0.20
cruz-clinton	1.22	0.95	1.49	0.00
fiorina-clinton	2.45	1.92	2.99	0.00
graham-clinton	0.40	-0.08	0.88	0.25
huckabee-clinton	1.90	1.44	2.36	0.00
jindal-clinton	0.93	0.26	1.60	0.00
kasich-clinton	2.31	1.97	2.66	0.00
omalley-clinton	1.51	1.06	1.96	0.00
pataki-clinton	1.44	0.81	2.06	0.00
paul-clinton	1.78	1.37	2.19	0.00
perry-clinton	2.39	1.69	3.10	0.00
rubio-clinton	0.97	0.75	1.18	0.00
sanders-clinton	2.85	2.67	3.04	0.00
santorum-clinton	3.94	3.38	4.49	0.00
trump-clinton	0.41	0.27	0.56	0.00
walker-clinton	2.67	2.15	3.18	0.00
webb-clinton	1.73	1.08	2.38	0.00
fiorina-cruz	1.23	0.66	1.81	0.00
graham-cruz	-0.82	-1.34	-0.29	0.00
huckabee-cruz	0.68	0.18	1.19	0.00
jindal-cruz	-0.29	-1.00	0.42	1.00
kasich-cruz	1.09	0.69	1.50	0.00
omalley-cruz	0.29	-0.21	0.79	0.89
pataki-cruz	0.22	-0.44	0.88	1.00
paul-cruz	0.56	0.09	1.02	0.00
perry-cruz	1.17	0.44	1.91	0.00
rubio-cruz	-0.25	-0.55	0.05	0.26
sanders-cruz	1.64	1.35	1.92	0.00
santorum-cruz	2.72	2.12	3.31	0.00
trump-cruz	-0.80	-1.06	-0.55	0.00
walker-cruz	1.45	0.89	2.01	0.00
webb-cruz	0.51	-0.18	1.19	0.49
graham-fiorina	-2.05	-2.75	-1.35	0.00
huckabee-fiorina	-0.55	-1.24	0.14	0.33
jindal-fiorina	-1.52	-2.37	-0.68	0.00

kasich-fiorina	-0.14	-0.76	0.47	1.00
omalley-fiorina	-0.95	-1.63	-0.27	0.00
pataki-fiorina	-1.01	-1.82	-0.21	0.00
paul-fiorina	-0.68	-1.33	-0.02	0.03
perry-fiorina	-0.06	-0.93	0.81	1.00
rubio-fiorina	-1.49	-2.04	-0.93	0.00
sanders-fiorina	0.40	-0.14	0.95	0.50
santorum-fiorina	1.48	0.73	2.24	0.00
trump-fiorina	-2.04	-2.57	-1.51	0.00
walker-fiorina	0.22	-0.51	0.94	1.00
webb-fiorina	-0.73	-1.55	0.10	0.18
huckabee-graham	1.50	0.85	2.14	0.00
jindal-graham	0.53	-0.28	1.34	0.75
kasich-graham	1.91	1.34	2.48	0.00
omalley-graham	1.10	0.47	1.74	0.00
pataki-graham	1.04	0.26	1.81	0.00
paul-graham	1.37	0.76	1.98	0.00
perry-graham	1.99	1.15	2.83	0.00
rubio-graham	0.56	0.07	1.06	0.01
sanders-graham	2.45	1.96	2.94	0.00
santorum-graham	3.53	2.82	4.25	0.00
trump-graham	0.01	-0.46	0.49	1.00
walker-graham	2.27	1.58	2.95	0.00
webb-graham	1.32	0.53	2.11	0.00
jindal-huckabee	-0.97	-1.77	-0.17	0.00
kasich-huckabee	0.41	-0.14	0.96	0.49
omalley-huckabee	-0.39	-1.02	0.23	0.78
pataki-huckabee	-0.46	-1.22	0.30	0.84
paul-huckabee	-0.12	-0.72	0.47	1.00
perry-huckabee	0.49	-0.34	1.32	0.87
rubio-huckabee	-0.93	-1.42	-0.45	0.00
sanders-huckabee	0.95	0.48	1.42	0.00
santorum-huckabee	2.03	1.33	2.74	0.00
trump-huckabee	-1.49	-1.94	-1.03	0.00
walker-huckabee	0.77	0.10	1.44	0.01
webb-huckabee	-0.18	-0.96	0.61	1.00
kasich-jindal	1.38	0.64	2.12	0.00
omalley-jindal	0.58	-0.22	1.37	0.54
pataki-jindal	0.51	-0.40	1.42	0.91

paul-jindal	0.85	0.07	1.62	0.02
perry-jindal	1.46	0.50	2.42	0.00
rubio-jindal	0.04	-0.65	0.73	1.00
sanders-jindal	1.92	1.24	2.61	0.00
santorum-jindal	3.01	2.15	3.87	0.00
trump-jindal	-0.51	-1.19	0.16	0.42
walker-jindal	1.74	0.91	2.57	0.00
webb-jindal	0.80	-0.13	1.72	0.20
omalley-kasich	-0.80	-1.35	-0.26	0.00
pataki-kasich	-0.87	-1.57	-0.18	0.00
paul-kasich	-0.53	-1.05	-0.02	0.03
perry-kasich	0.08	-0.69	0.85	1.00
rubio-kasich	-1.34	-1.72	-0.97	0.00
sanders-kasich	0.54	0.18	0.90	0.00
santorum-kasich	1.62	0.99	2.26	0.00
trump-kasich	-1.90	-2.23	-1.56	0.00
walker-kasich	0.36	-0.24	0.96	0.86
webb-kasich	-0.59	-1.30	0.13	0.30
pataki-omalley	-0.07	-0.82	0.69	1.00
paul-omalley	0.27	-0.32	0.86	0.99
perry-omalley	0.89	0.06	1.71	0.02
rubio-omalley	-0.54	-1.01	-0.07	0.01
sanders-omalley	1.35	0.89	1.81	0.00
santorum-omalley	2.43	1.73	3.13	0.00
trump-omalley	-1.09	-1.53	-0.65	0.00
walker-omalley	1.16	0.50	1.83	0.00
webb-omalley	0.22	-0.55	0.99	1.00
paul-pataki	0.34	-0.39	1.07	0.99
perry-pataki	0.95	0.02	1.88	0.04
rubio-pataki	-0.47	-1.11	0.17	0.51
sanders-pataki	1.42	0.78	2.05	0.00
santorum-pataki	2.50	1.67	3.32	0.00
trump-pataki	-1.02	-1.65	-0.40	0.00
walker-pataki	1.23	0.44	2.02	0.00
webb-pataki	0.29	-0.60	1.17	1.00
perry-paul	0.61	-0.19	1.42	0.42
rubio-paul	-0.81	-1.24	-0.38	0.00
sanders-paul	1.08	0.65	1.50	0.00
santorum-paul	2.16	1.49	2.83	0.00

trump-paul	-1.36	-1.77	-0.96	0.00
walker-paul	0.89	0.25	1.53	0.00
webb-paul	-0.05	-0.80	0.70	1.00
rubio-perry	-1.42	-2.14	-0.70	0.00
sanders-perry	0.46	-0.25	1.18	0.74
santorum-perry	1.54	0.66	2.43	0.00
trump-perry	-1.98	-2.68	-1.27	0.00
walker-perry	0.28	-0.58	1.14	1.00
webb-perry	-0.67	-1.61	0.28	0.60
sanders-rubio	1.89	1.65	2.12	0.00
santorum-rubio	2.97	2.39	3.54	0.00
trump-rubio	-0.55	-0.75	-0.35	0.00
walker-rubio	1.70	1.17	2.23	0.00
webb-rubio	0.76	0.09	1.42	0.01
santorum-sanders	1.08	0.51	1.65	0.00
trump-sanders	-2.44	-2.61	-2.27	0.00
walker-sanders	-0.19	-0.71	0.34	1.00
webb-sanders	-1.13	-1.79	-0.47	0.00
trump-santorum	-3.52	-4.07	-2.97	0.00
walker-santorum	-1.27	-2.01	-0.53	0.00
webb-santorum	-2.21	-3.05	-1.37	0.00
walker-trump	2.25	1.75	2.76	0.00
webb-trump	1.31	0.67	1.96	0.00
webb-walker	-0.94	-1.76	-0.13	0.01

Appendix B: MTurk Questions

Sex Wording: What is your gender?

	Male	Female	Other
Number of Respondents	1627	1096	11

Age Wording: What is your age?

	18 – 24	25 – 34	35 – 44	45 – 54	55 – 64	65 – 74	75 – 84	85 and older
Number of Respondents	368	1122	625	307	209	90	10	2

Employment Wording: What is your employment status?

	Full-Time	Part-Time	Unemployed	Retired	Student
Number of Respondents	1798	356	297	114	169

Race Wording: Please choose one more races that you consider yourself to be.

	White	Black	American Indian	Asian	Hawaiian or Pacific Islander	Hispanic, Latino, Spanish	Other
Number of Respondents	1685	148	51	590	7	220	33

Education Wording: What is your education level?

	Less Than High School	High School Graduate	Some College	2 Year Degree	4 Year Degree	Professional Degree	Masters and/or Doctorate
Number of Respondents	13	155	383	232	1268	196	487

Political Interest Wording: Generally speaking, how interested are you in politics?

	Extremely Interested	Very Interested	Somewhat Interested	Slightly Interested	Not At All Interested
Number of Respondents	547	987	819	294	87

Partisanship Wording - Branching question: Generally speaking, do you usually think of yourself as a Republican, a Democrat, and Independent, or what?

Follow-up wording: Would you call yourself a strong {piped from previous question} or a not very strong {piped text}?

	Strong Democrat	Democrat	Weak Democrat	Independent	Weak Republican	Republican	Strong Republican
Number of Respondents	609	501	286	422	193	355	287

Ideology Wording: When it comes to politics, do you usually think of yourself as extremely liberal, liberal, slightly liberal, moderate or middle of the road, slightly conservative, extremely conservative, or haven't you thought much about this?

	Extremely Liberal	Liberal	Somewhat Liberal	Moderate	Somewhat Conservative	Conservative	Extremely Conservative
Number of Respondents	360	763	421	439	305	283	121

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