Mean Tweets

An Analysis of Average Negativity in the 2016 US Presidential Campaign

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Abstract

The 2016 US Presidential Election is not just notable for its result, but for the historic mediated setting that provided the backdrop. This was not the first election to see widespread adoption of social media as campaign tools, but 2016 arguably saw some of the highest attention paid to the activity of the candidates in this medium. This paper will explore how the major party candidates used the micro-blogging website, Twitter, and more precisely how campaign negativity was expressed by both the candidates and the rest of the tweeting population. Conducted from the 26th of September to the 9th of November, this study hypothesized contagious and corrective phenomena between the major party candidates and the rest of Twitter. While some of the results of this exploration reaffirmed extant theory about campaign negativity, there were additional interactions between the variables that indicate that negativity is expressed differently in a social media setting. This paper chiefly found that Donald Trump, though a more frequent target of higher degrees of negativity, was also able to elicit more criticism of his opponent than Hillary Clinton was able to provoke towards Trump.

Introduction

On June 16, 2015, in front of a tower bearing his name, Donald J. Trump announced his candidacy for President of the United States. Just two months earlier, Hillary Clinton made a similar announcement when her campaign released a video of average Americans saying they were with her. A year and a half later, Trump stood as President-Elect after a campaign season defined by its vitriol, surprising results and a mass media circus. As the new leader planned his cabinet and first 100 days in office, the media at large reflected on its role in mediating the dialogue between candidates and voters. *The New York Times* sent a letter to its subscribers

acknowledging the intensity of the cycle and pledging to rededicate themselves to reporting the world "honestly, without fear or favor, striving always to understand and reflect all political perspectives" (Sulzberger 2016). Meanwhile, Facebook CEO Mark Zuckerberg fended off criticism at a technology conference as journalists accused his company of not policing fake newspapers (Burke 2016).

The news media, new and old, are now soul-searching in an attempt to find where their reporting might have been unfair or even potentially hazardous for the election. Regardless of their findings, this election presented specific challenges outside of the personalities and policies of each candidate. 2016 saw an even more digitized election play out over millions of screen both nation, and worldwide. Social media was no longer just a novel and hip way to connect with younger voters. It instead became a central tool that both sides used extensively to mobilize and engage voters across various demographics. As the election shifted to be discussed and debated across more social media outlets, so did many controversies. For example, a popular meme of a frog, named Pepe, became designated a hate symbol by the Anti-Defamation League as alt-right blogs and websites used derivations of the meme to create anti-Semitic and racist messages (Pepe 2016). Then, as the race reached its competitive height, the news reported that both campaigns shifted into full negativity mode releasing a blitz of new ads designed to levy accusations based on new controversies in the ever-evolving media landscape (Simendinger 2016).

On November 8, in the final hours of the night, the race was called as Donald J. Trump carried the Rustbelt: an upset to most pollsters who projected a solid Clinton win. Each campaign's negativity, and the new media that their messages and ideas were transmitted over, contributed to the specific tone and perhaps outcome of the election. What this study hopes to

provide is an insight on how these two contributing factors interacted. To do so, this paper seeks to identify and document a relationship between the social media campaign strategies of both major party candidates and the mass audience that consumed and demanded the media cavalcade that made 2016. Speaking more specifically, this study looks to the micro-blogging site Twitter and the negative political messages transmitted by @realdonaldtrump and @hillaryclinton. By tracking each account's daily amount of negative content, and then comparing this rate to the amount of negativity towards each candidate from a sample of other users on Twitter, this study hopes to link the sentiment of the campaigns to that of the electorate expressed over Twitter.

Literature Review

Mass Media and Public Opinion

Before even beginning to approach social media's role in the most recent election, it is essential to understand early criticisms of mass media. One of the most profound and still relevant critics was Walter Lippmann whose seminal work *Public Opinion* raised serious questions about the role of mass media in informing the public and how the public, in general, formulates opinions and preferences. Additionally, *Public Opinion* warned of the potential new abilities of governments to sway the public due to the advent and spread of radio. Fundamental to this understanding of public opinion was the notion that there exists a separation between the authentic and real world, and the public's views and opinion about the same. News media, while seeking to inform the public, actually misleads them to a certain extent. Lippmann specifically cites the prevalence of stereotypes to summarize and simplify complex notions like other cultures and countries (Lippmann 1922). In his view, the world was too big and complex for any person to directly engage. To make it more complicated, this author shared additional skepticism of the mass media's ability to relay accurately the size and complexity of the world. For in

attempting to do so, the mass media would "have to describe and judge more people, more actions, more things than we can ever count, or vividly imagine" (95). Also, there is not only too much information to relay to everyone but also the mechanism to do so, could be easily abused to craft particular opinions on subjects. Lippmann points to the prevalence of stereotypes to define and conceptualize other cultures. The initial fear of this author was the emergence of government-controlled mass propaganda via the radio. The ability of a single voice to inform millions of the world around them would make a "pseudo-environment" whereby people occupying the same world are separated by their understanding of each other as informed by new mechanisms of mass communication.

Offering opinions that could be used to defend Twitter is Lippmann's key critic John Dewey who countered that *Public Opinion* essentially advocated for elite media leadership over the easily swayed and deceived public. In *The Public and its Problems* this author presented a specific view on how publics form and approach issues. Dewey contended that a public actually only forms out of "a common interest in controlling … consequences" (126) and thus is contingent upon the collective problems faced by groups of people. He goes further to claim that because of this, no two publics are the same for their composition is based on their specific time and issues. Yet where Dewey disagreed with Lippmann is the potential for the public to be able to solve the issues that it encounters through communication. Lippmann contended that there was an inherent risk for even a public formed out of shared problems, to be manipulated and control by larger interests, which would in turn threaten the very roots of democracy.

By comparison, Dewey thought that manipulators could be circumvented or entirely defeated by greater communication. Where the more skeptical Lippmann saw the power of the mass media being abused, Dewey held that it would liberate people from the problems that

prevented democracy from solving issues. It is important to note that these rival theorists, though in disagreement on the potential harms and benefits that mass media could provide the public through information, both acknowledge, or at least argued with tacit acceptance, that mass media could directly affect public opinion. Lippmann contended that consent could be artificially manufactured while his rival stipulated that more advanced communication technology could cause a great reengagement with political discourse. Specifically, Dewey thought that the self was emboldened by the shared experiences of symbols and the establishment of shared meaning. By creating shared meaning, with the revival of local, face-to-face community, there would be no limit to how much people could increase their own understanding of the world and self (216). This vitalized connection between members of a local community, where information would be liberated from the direct flow that Lippmann feared could be used to throttle obedience, would serve as the active hedge against threats to democracy.

To apply this understanding to the current context, both opinions have a direct application to Twitter and the observations collected in this study. With the dynamic of followership and hashtags to index information, one could argue that the micro-blogging site is ripe for a controlling class of mega users that dictate the perspective of the whole through a massive network of followers and retweets. A firm counter claim can also be lodged that the site is too big for such manipulation and that the technology that Dewey predicted and hoped for is here now. The site now produces nearly half a billion new tweets every day ("Twitter Usage Statistics") and is growing at a capacity of nearly 30% annually. Is the site too big to manipulate, or does its inherently large size make it so that an elite usership can effectively direct the media ingested by millions by gaming virality? The answer is more complicated than what a simple look at what the growing capacity of Twitter would indicate. First, while the top percentile of

Twitter users have follower counts nearly a hundred times larger than the average user (Bruner 2017), it is a well established fact that grassroots social movements can help produce and disseminate some of the most retweet hashtags (Commentary 2015). Furthermore, the majority of tweets about a subject are original though they use content published by elite accounts. The balance of power between the famous accounts with the top level of followers and the vast majority of average accounts with each individually a slim portion of the attention of the Twittersphere, creates an interesting social sphere that defies descriptive and simple categorization by the two thinkers discussed. This makes it even more important to continue to understand the evolution of communication theory and how it may apply to this new medium.

Continuing forward nearly two decades after the debate sparked by Lippmann and Dewey, new observations led Lazarsfeld, Berelson and Gaudet to entertain a more subtle mechanism behind public opinion. Deviating from direct effects, these authors postulated that additional actors could actually facilitate media influence. This theory, known as the two-step flow model, holds that elite actors influence opinions in conjunction with the mass media. In this model, the news media are followed most closely by opinion leaders who then, in turn, give signals to the greater public on how to feel about the issues reported by the media (Lazarsfeld et al 1948). These observations came out of the 1940 presidential race and focused on interpersonal effects, as opposed to direct effects the news media had on any individual person. The authors found that "opinion leaders" formed in their own communities as people with the highest understanding and attention to the news. These leaders would exert their personal influence to shape how those around them understood the news.

While this might have put Lippmann's fears to rest about a propagandistic government with monopolistic control over mass media, the two-step flow model brings up even more

complicated questions about how public opinion is formed in a democracy. Specifically, if Twitter is as open a public forum as it professes to be. An initial look at how news media accounts publicize events as compared to how individuals promote stories quickly shows that social media facilities one-step, two-step and multi-step flows of information to individuals. Take for example a study conducted by the Pew Research Center and George Washington University. When data was pulled from both popular news accounts and general users, it was seen that news sites only retweet information 7% of the time while users that tweeted about the news, rarely produced purely original tweets that didn't use media retweeted from other accounts (Pew 2016). Emphasizing this was a study conducted that tracked 150,000 tweets from environmental movements in Chile. This study found that while a vast majority of mentions (nearly 90%) were direct at media outlets and official protests voices, nearly 20% of all mentions over the platform contained personalized messages directed at the user (Hilbert). What these studies show together is that while media accounts are widely received directly, the interaction between users and both regular and popular accounts seem to indicate a simultaneous multi-step flow of information. Twitter, as a medium, is not bound strongly to any flow but instead enables multiple streams of information to form between accounts.

Additionally informing the two-step flow were the ideas of agenda setting and framing. McCombs and Entman, respectively, added to the understanding of public opinion by considering that the selections of certain stories over others, and the juxtaposition of stories to each other, created the issues that the public deemed important. The agenda setting that McCombs discussed was primarily focused on how the media's choice to report on some candidates over others resulted in a subtle and perhaps unintentional form of media anointment. Only the candidates that spoke on the issues that the news media found most important would be

covered and given time (181). Applying this idea to the greater world of news stories, and it could be understood that a new station choosing to cover, say a landslide over the dipping price of oil, could in fact impact the way the public considers mountain road safety over fuel emissions. This theory holds that the media, while not particularly capable at manipulating the public opinion on specific issues, can in fact set the salience and order of importance for issues. In other words, the media actually is not incredibly adept in telling the public exactly what to think about the issues, but does a tremendous job making sure that the public considers some issues over others. This theory draws heavily from Lippmann's understanding of the limited nature of human understanding in the large world.

Entman added to this understanding by discussing how not only the selection of some stories over others but how by emphasizing specific characteristics or details of a story over others, could subtly impact the way that the public considers issues (54). Choosing the perspective, or "framing" the issue, meant that the media could potential manipulate the public's understanding of issues by approaching them differently. To extend the example of the previous paragraph, after choosing to run the landslide over the oil boom, the media additionally chooses to highlight the frequency of road inspections and the how receding tree lines disrupt sediment. Any viewer of the broadcast would think that lack of government inspection and forestry protection is a salient issue worthy of their attention. A media skeptic like Lippmann could interpret framing as the potential mechanism of abuse in propaganda systems whereby the truth could be openly discussed but framed in such a way to reduce or eliminate the public concern of said issues. For example, the news could report on the a catastrophic war in a distant country, but discuss the gory details like body counts, massacres and refugees from an international trade perspective only realizing the human costs in terms of an affected economy.

Beyond McComb and Entman, there have been countless theorists who have extended these theories to more modern mechanisms of mass communication like TV (Gamson 1992) (Iyengar 1982). Others have experimented with the possibility of ordering and moderating the effects of framing and agenda setting by applying the two-set flow model (Borsius 1996). Needless to say, the potential effects of news media on public opinion is an ever evolving and considerate field of study that looks to understand how more modern and newer forms of media can affect the public. One such theorist is Hernando Rojas whose theory of "corrective action" (2010) adds specific insight into how modern mass news media can affect the public. In this theory, Rojas considers the existence or perception of a mainstream media and the pressure it exerts on people who hold opinions and ideas contradictory to the mainstream. Previous authors stipulated that in response to such pressure an individual could reject the media and continue to hold their opinion, accept the media's opinion or disengage from the issue and no longer have any stance. Rojas added the fourth option of "corrective action" whereby an individual would not just retain her original opinion but would actively seek out ideas contradictory to the mainstream (345). The individual would look to "correct" a bias that she perceive in the mainstream and could lead, when considered for an entire public, to a section of a population rejecting and then actively contradict an institution specifically designed to inform them.

<div align="center"><u>Campaigns and Negativity</u></div>

Before continuing, it is important to define exactly what is negative campaigning. The debate on this subject, while ongoing, will be confined in this paper to focus on larger issues related to social media use. Thus the definition presented by David Geer from *In Defense of Negativity* will be used and defines negativity as "any criticism leveled by one candidate against another during a campaign" (Geer 2006, 23). The definition may be construed as being overly

inclusive but in fact it focuses exactly on what this study is concerned with—does the conduct of the candidates towards each other affect the behavior of the public and more specifically, does the greater public (or in this study, Twittersphere) emulate or copy the tone of the candidates? Other definitions might be more exhaustive and complex but Geer's simplicity allows for this study to quickly and effectively identify the campaign messages that are theorized to have a definitive media effect on the public.

News media, regardless of our understanding of effects, has a fundamental responsibility in democracies during the election season. The democratic process in the United States has evolved alongside widening mass communication mechanism and politicians were quick adopters of new methods to get out their messages (Coleman 2006, 170). News media, has therefore in its role, been a conduit for this essential democratic process. Lippmann's fears of the press manipulating or biasing the mass public in certain directions has given rise to the Federal Communication Commission's (FCC) Fairness Doctrine whereby media outlets had to provide an equal amount of time to issues in an "honest, equitable and balanced fashion" (HR 501). Constitutional challenges based on free speech eventually eroded this rule and has left the equal-time rule that applies only to candidates and exemptions are given to talk shows and other syndicated news programming.

This is important to note as the discussion turns to campaigns and their messages. There has been a concerted and concentrated effort to ensure that media outlets cannot unfairly influence voters and furthermore, that candidates can have equal access to the vectors of mass communication. Yet these candidates, once able to fairly and equally get their message out to the public, also pose a potential to harm the democratic process. Or at least, that is the reasoning behind authors like Ansolabehere and Iyengar who in 1994 argued that the specific messages of

a campaign could in effect, demobilize voters and discourage participation in the process. Their primary concerns revolved around the effects of messaging and more specifically negative campaigning. While it was previously (and to an extent in modernity) worried that the media itself, with its monopolization over information, could sway opinions in a democracy, these authors chiefly worried about how the democracy itself could be made less functional. These authors are additionally operating off of assumptions about the election process whereby the deliberative process of selecting candidates and voting is contingent upon civility (Sanders 1997, 348). This reasoning holds that if voters are not able to deliberate together in mutual respect, then they will end up voting along more partisan and emotional lines. In *Going Negative*, Ansolabehere and Iyengar contrasted years of high voter participation to low years and discussed in more detailed ad-checkers and the informative value of ads. While concluding that advertisements, even negative ones, could inform public opinion, the cost of doing so could be too high. The chief concerns of these authors were the demobilization effects whereby voters find ads so negative and reductive that they just tune out entirely (Ansolabehere 110).

However frightening the idea of a demobilized public can be, it should be noted that Iyengar and Ansolabehere were actually critics of existing literature and accepted theory. The understanding of campaign negativity was that while potentially unseemly, that this type of political expression was neither novel nor uninformative. On the contrary, authors like David Geer have steadily built up an understanding of negative political messaging wherein negativity is an enlightening facet of the democratic process. What they have found is that negative appeals have a greater informative value for "candidates will be less able to duck issues and their stated views on other issues will be subjected to scrutiny" (Geer 14). In this way negativity is an enlightening mechanism that does not just inform the most active of citizens, but also allows

even weakly committed and poorly informed voters to understand candidates for issues they care about (Kelley 1956). However, it is important to note that Geer admits that if the political discourse devolves into only name calling, than it no longer serves its purpose and "does the damage its detractors fear" (Geer 17).

The case on negativity is far from settled though. There are still studies that actively contest the assumption that negative advertising provides more in terms of information and scrutiny than what they cause in terms of demobilization and incivility. Malloy and Pearson-Merkowitz disputed the relative power of negative ads to positive ones by conducting a national study of Congressional House races (34). Scouring media markets and archives for as many political ads as possible, this study demonstrated that predominantly positive races did marginally better than races with an even mixture of ads and those races with predominantly negative advertising. Conversely, a study from the *American Political Science Review* levies criticism at the Iyengar and Ansolabehere study by attempting to replicate the same results with a later political cycle. This study conducted by Wattenberg and Brians concluded that the previous study "is deeply flawed and … exaggerated the demobilization dangers posed by attack advertising" (Wattenberg 898). Currently, a preponderance of evidence lies on the side of negative campaign ads that supports their use and finds in them greater information utility. However, this is not to say that the debate is over. Information demobilization factors are still hotly contested but the informative effects of negativity helps to set this study on a solid foundation. This is due to the fact that both sides readily agree that negative ads have an informative quality that many positive ads do not and for a study that hopes to specifically explore how negative messages are considered in a novel medium, this agreement in the extant literature is extremely useful.

Up to this point in the exploration of negative messaging, certain tenets of mass

communication and negative political engagement have been held as constants. One of the first

assumptions is that the organizations of mass media (radio and TV stations, news outlets and the

infrastructure associated with each) play a major role in connecting voters to candidates. Second,

it has also been accepted that negative advertising has traditionally been directed at inadvertent

audiences. In newspapers and on television, your regular morning read or scheduled show would

be interrupted by an ad on the side of the column or on the screen. These were inescapable and

were the cost of consuming media. While it would be easy to contend that this changed with the

internet, in truth, the world wide web didn't change the dynamics of inadvertent advertisement.

Visiting a webpage, a user could be greeted with a new set of invasive ads that instead of just

showing up at the side could pop up on the screen and even under the user's cursor. The real

seismic shift in the relationship between ad and watcher occurred with the rise of social media.

Instead of this medium being defined by the type of content it can share or the amount of people

participating, social media has been defined by its dispersed nature. In most social media

technologies, the user's ability to share information widely and for any other user to act as an

amplifying node has been a defining factor when compared to more traditional media. This

factor of social media was confirmed by one of the firsts tests to capture a full picture of the

entirety of the Twittersphere by Kwak, Lee, Park and Moon. These researchers were able to take

a full crawl of the nearly 41 million users that existed at the three-year-old platform and

determined that, at the time, favorite count was not a clear indicator of content produced. By

linking instead to the amount of retweets an account can generate from other users, Kwak et al.

proved that dispersion and sharing of extant information correlated more closely with generating

content that is shared widely (Kwak 2010, 595). In other words, the popularity of an account was a weaker determinant of how viral the messages the account created could be as compared to how frequently the account retweeted and passed on content generated from other users.

In an attempt to understand the attractiveness and utility of such open networks to campaigns, Gulati and Williams attempted to track the congressional adoption of Twitter accounts between House and Senate contenders between 2006 and 2012 (38). While they were able to track the rise of Twitter between 2006 and 2008, they concluded by 2010 that with nearly 90% of both congressional bodies adopting the social media platform, that the study had reached its ceiling. While both authors speculated as to the reasoning behind the surge, they concluded that content published to social media sites offered a rare voluntary political interaction with negative ads. Instead of placing thousands of dollars of media buys in key markets, the clever politicians with Twitter accounts could release the same ad as those intended for television media markets. However, now posted to Twitter, it would be up to the users to play the commercial and engage in the campaign messaging. This means that voters voluntarily watch negative videos and through their own portals, seek out the messages they want to hear (49). This isn't even to mention the retweeting and sharing that has, to a degree, supplanted ad markets as a way of distributing content. Not only do users get to pick what ads they watch, but they can also choose to pass on the information and expand a free publicity network for politicians.

This distinction is essential to this paper, as it provides the largest paradigm shift from previous understandings of negative advertising. Critical arguments about a disengaged and demobilized voter base seem less legitimate in a setting where the voter can actively choose what information they take in. Additionally, support for negative messaging must be caveated when the actual structure of social networks, like Twitter, becomes apparent. Instead of tuning into a

channel that follows FCC regulations about equal access, a potential voter's Twitter account is populated by friends, popular celebrities and strangers. These networks then produce content that the user is most likely to like and agree with (Prior 1997, 130; Sunstein, 2001, 32). These "echo chambers" ensure that users aren't exposed to negative political advertising that attacks their candidates and thus do not get the full information utility discussed by Geer and other authors.

This isn't to say that social media cannot benefit the electorate. An interdisciplinary study involving Facebook employees found that using the formed networks on the social media site in question, users were influenced to vote by seeing the amount of people in their network who voted. The 2010 study provided some users with a button to press, which would post that they voted to their timeline for the members in their network to see. Another set of users were given the same option but could see how many of their friends voted before pushing the button to display on their own timeline (Bond et al. 3). The study found that "providing social endorsement cues increase participation more than providing information alone" (21) and that existing trends in voting were also found online, like the suggestive relationship between users being more educated and users being more likely to vote based on being exposed to the "friends who have voted" side of the experiment.

Next, Eshbaugh-Soha contends that social media, while slightly more negative in coverage than traditional media, follows similar patterns to its predecessors. Mainly, social media coverage follows the major events, both scheduled and not, through the campaign cycle (147). This creates a specific situation where social media coverage of events follow similar rules as traditional media coverage, but diverge in their outcomes. Social media is quicker, more negative, and with micro-blogging sites like Twitter, the medium can create more succinct messages that are consumed more regularly than traditional news. Some authors are quick to

point out that these divergent factors may be the most important and defining ones for journalism and news reporting. Regina Lawrence probed this dilemma in more detail and after interviewing journalists who were covering the 2012 Republican primaries along the east coast. The questions this author asked focused specifically on the effects that journalists have seen on their work since the emergence and adoption of social media. Concerns were generally around how little vetting of sources and how dangerously quickly information could be distributed (107). Furthermore Lawrence found a relative reticence to adopt social media finding that while a plurality had accepted the new tool into some of their work, many had either rejected its use or used it sparingly.

A final factor of social media to consider is how it has broken down traditional insights on elite versus mass political participation in polarization. The critique that Abramowitz and Saunders made in 2008 immediately come to mind when these authors contested the claim that polarization was a myth. By examining heightened levels of political participation in the 2004 election, and then considering survey data that shows a widening gap in political ideology, the authors concluded that the wedge between parties could not only be explained by elite polarization (553). Now consider the environment that a social media site like Twitter creates. There are clear distinctions between elite users and others and this is mostly centered around their status outside of Twitter. Celebrities usually gather more followers and friends than average people and accounts related to publications usually have fewer friends for direct communication and more followers to publish content to. However, a follower could subscribe to a reality TV celebrity, a major news publication, a gossip column, their co-worker and a presidential nominee and receive all their tweets on the same level. Each tweet would show up on their feed based solely on the time they were published and not filtered for their respective popularity.

With this understanding a study conducted by Coffey et al. gains additional credibility. These authors predicted that online postings of newspaper publications in more competitive states in the 2012 presidential election would have more uncivil comments then those in less competitive states. Accounting for multiple factors like contentiousness of story, number of elite quotes, and number of comments, the study found clear evidence that the more contested state (Ohio) had, ceteris paribus, a notable and statistically significant higher level of incivility compared to the less competitive state (Wisconsin) (261). These authors utilized the "spill over" theory which stated that political incivility could transfer to different political expressions and even different mediums. Coffey et al. predicted that simply being more competitive led to more ads to be made in a state, which would lead to more negativity "spilling over" into the comments of a local publication. When applied to social media, the question could be asked if exposure to certain levels of content inside an existing social media platform can in fact influence content created in that platform.

Social Contagion

The question posed in the previous section was the subject of a controversial but incredibly important experiment in this field of study. In 2011, Facebook intentionally manipulated the information feeds of 689,003 users to show content with certain emotional states and additionally tailored advertising to also show similar emotions. The evidence suggested that exposing users to more or less negativity or positivity resulted in a corresponding change to the content that users produced (Kramer et al. 2014). This study directly contradicted previously held theory that interactions with people could influence moods more than interactions devoid of direct contact. This study also effectively confirmed several implications that arose from the Coffey study: chiefly that not only can sentiment be passed along and expressed in different

media but it could also circulate inside a single platform and then be expressed. Yet unlike the Coffey study, the mechanism of dispersion on Facebook was far more complex and defined by theories surrounding social contagion.

Now social contagion is best understood as a series of mutually informed observations about phenomena rather than a unified and cohesive theory. The Stanford review of the subject reads similarly and concludes that "rather than generating and 'having' beliefs, emotions and behaviors, social contagion research suggests that … those beliefs, emotions and behaviors 'have' us." In this sense, behavioral social contagion is involuntary political expression. So when the Kramer study found an average of a few less negative words posted over a week after exposure to more positive content, the natural explanation was that people were changing their expressions without knowing. Criticized for its invasiveness, the Facebook study confirmed the prime vector for contagion transmission. When done subtly, the user will not even know they are being affected.

These findings seemingly contradict existing understanding of political behavior as examined by political psychology. However, upon closer examination, the context of behavioral social contagion is far more limited than the content that political psychology cover. Political psychology attempts to understand political behavior as typically costlier and more involved than anything that could be done on social media. The Oxford Handbook on Political Psychology cites foreign policy decisions, reactions to terrorism, contemplation and support for public policy and voting as all-important applications of its field (Sears 2003, 1). Meanwhile, the Yale News explored studies at the publication's resident institution that tracked the spread of ideas across the globe and into mass political action (Dodson 2016). The difference between the political psychology understanding of events and the contagion theory understanding is the scope of user

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action. The former attempts to shed light on the cognitive processes associated with political decisions, while the other attempts to trace how political actions are linked to each other.

Now by understanding behavioral contagion theory in definite political psychology terms, we find the concept of on-line and memory-based processing models. Both models are attempts to understand how people form opinions about issues and candidates. The former method describes instant decision-making backed by a running tally of "good" and "bad" impressions that exist in a bidimensional unipolar judgment system. By comparison, memory-based processing functions off of deeper memories where interactions are judged along a spectrum of "very good" to "very bad" thus making this method unidimensional bipolar categorization (Levine 2002). These two ideas may seem divergent, but other authors have proposed a melding of the two to form a new theory whereby interactions are considered in context to each other, but positive and negative interactions are judged separately. A "bad" political ad about a politician will be judged against previous "bad" impressions and will form a new impression from this judgment (Kim 2016). This theory shares a faint similarity to heuristic models but instead of party identification or family informing choices, a backlog of previous impressions and their relative weights inform combined on-line and memory based processing.

When viewed in the context of Twitter, there are few theories that inform behavioral social contagion analysis as the theories discussed previously. As a person reads through tweets on their feed they will be judging potentially hundreds of tweets, or direct messages, to make their next choices. The fast-paced, low-capacity platform Twitter provides naturally encourages fast thinking to keep up with the constant stream of information. Deciding to like or share something will be a choice dependent on a long list of past choices that are best summarized by the current standing of the account and the satisfaction the user has with the content. In applying

this combined model of processing, behavioral social contagion becomes more likely. Sorting

through and deciding between hundreds of tweets, can subtly impact the content creating habits

of the viewer.

Theory and Hypothesis

It is near impossible to discount the effect that social media has on the democratic

process. Conversely, it is also out of reach to propose a model that is applicable across platforms,

users and situations. This leaves the current situation ripe for exploration and critical analysis. To

date, multiple studies have attempted to use Twitter as a predictive tool to call elections (Hosch-

Dayican et al. 2014) (Tumasjan 2010) (Sharp 2012). Other investigators have focused on how a

thorough investigation of the meta-data associated with an account can reveal strategic

information about campaign strategy (Robinson 2016). It is also now standard for mass media

publications to dedicate entire sections of their website and staff to examining digital data like

the New York Times Upshot or the stand-alone 538 blog. With all of this analysis there is still no

unified theory on how social media precisely reflects public opinion or how it contributes to

forming it, though there have been important insights drawn about Twitter as a platform (Ferrera

2015).

Based on the literature examined, there is a clear gap in study concerning negative

campaign messaging and its impact on Twitter users. By additionally understanding the

constraints and uniqueness of Twitter, this study can hypothesize how users would approach and

potentially share negative content. Informing this will be the knowledge of both political

psychology and social contagion theory. In this way, this study considers the setting that the data

is exchanged in (Twitter as a medium), the specific nature of the messages transmitted

(negativity as a message), the processing patterns of users (on-line and descriptive processing)

and the subtle factors that impact the spread of messages (behavioral contagion theory).

However, examining the data collected for this study properly means not only relying on

previous research but also examining communication theories that were not theorized with social

media primarily in mind. As explained in the previous sections, while social media presents new

possibilities, it operates with many of the same dynamics as more traditional media. The theory

of "corrective action" is just one such extant idea that focused on reactions to overwhelming

messaging from mainstream media (Rojas 2010). This theory went beyond the understanding of

how unpopular opinions react to criticism from the mainstream media by explaining a new

reaction. First rejecting the views of the mainstream media, but then actively seeking out sources

that are against the prevailing reporting as a personal way of balancing or "correcting" a

perceived information discrepancy characterize this "corrective action."

  While Rojas's theory of corrective action would explain differences in reaction to Clinton

(as a mainstream media favorite) as compared to Trump, there are additional theories that would

explain a simple positive relationship between a candidate's negativity and the public's.

Facebook itself made the most invasive but fruitful exploration of a simple positive relationship

between exposed and produced content in its feed manipulation study (Kramer). Facebook

discovered that by changing the content of a user's feed and their advertisements, users generally

created content with more words (positive and negative) consistent to the content they were

exposed to. This, if seen in the data collected, would represent a "direction action" between

candidate and user, as the sentiment of one would be transferred to the other. This theory is

rooted in an understanding that content production is directly linked to content exposed. This

study is only examining in detail two accounts and projecting that either individual candidate

could influence the tenor of all of Twitter is ludicrous. Instead, "direction action" will assume

that the major party candidates participated in active signaling to campaign surrogates and other accounts closely related to the campaign. Trump or Clinton going negative would then be passed along to the accounts used to primarily campaign and drive voters (while this could be social media accounts like "dems4hillary" these accounts can also be of important allies like @mike_pence). In this way, we would see a major party candidate, and their associated allies, set a daily tone that would then trickle to users who would then follow suit. This assumption is reinforced by observations of independent political actors' social media use that show that both Democrat and Republican supporting actors generally act as online surrogates during the campaign but defect to promoting their own specific messages after the campaign (Azari 2015, 68).

The final theory to consider is offered by Coffey, Kohlert and Granger in their work published in "Controlling the Message." Their writing on incivility focused on the different environment that social media provides, like the lower cost for engaging online versus engaging the-real world campaign activity. The more important idea put forth by Coffey et al is the potential of this new medium to create an environment where opponents cannot "recognize the moral standing of those whom they disagree" with (Farrar-Myers 251). These authors fear that that anonymity, low cost speech, and superior information selection will lead to insulated opinions with people unable to engage civilly among issues. If unchecked, it would lead to a "spiral of silence" (Noelle-Neumann 1974) whereby competing parties could become increasingly isolated from each other and thus making the costs of negativity lower. This spiral is a positive feedback loop whereby fear of deviating from the dominant or accepting opinion pushes those with alternative views to not express them. Knowing that Twitter users have a superior level of self-selection, this could mean progressively, positive added effects, which

would be akin to internal "spill over" run out of control. Instead of taking queues from a major party candidate and their surrogate messengers, a Twitter user would be catalyzed by other accounts also copying the sentiment of major-party candidates. In other words, after being prompted by the negativity coming from the campaign, users would continue to take queues from fellow users also affected and create a self-sustaining and increasing cycle of negativity.

These observations and theories have helped to create the following hypotheses and variables:

Independent Variables: the sentiment of the major party candidates towards each other as determined by the content of their tweets

Trump's Sentiment (collected from @therealdonaldtrump)

Clinton's Sentiment (collected from @hillaryclinton)

Dependent Variables: the sentiment of Twitter users towards the major party candidates as determined by lexicon analysis of tweet content

Twitter's Sentiment towards Trump (tweets referencing Trump)

Twitter's Sentiment towards Clinton (tweets referencing Clinton)

H(0) NULL: The negativity towards the candidates and the negativity of the candidates will not correspond to each other and will appear random.

H(1) CORRECTIVE ACTION: Negativity towards Clinton will be more determined by her own levels of negativity than her opponents. Twitter users will identify her as the "mainstream candidate" and will attempt to "correct" her messaging by responding to her negativity with negativity.

H(2) SPILL OVER CYCLE: Negativity towards the candidates will be generally and relatively higher than the candidates themselves and will accumulate over the campaign unless there are several consecutive days of positivity to dull the feedback cycle of the general Twitter users themselves promoting the negativity.

H(3) CONTAGIOUS EFFECTS: Negativity towards the candidates will generally correspond to the negativity expressed by the candidates. While negativity may be relatively higher or lower, the changes between each day, for the general public, will show correlation to the changes made between each day by the campaigns. This differs from positive messages, which may not have the same dispersion and communicability between users.

Research Design

To test the listed hypotheses, data was collected between September 26 and November 9, 2016. The Associated Program Interface (API) used to collect data is a code provided by Twitter. This API is a streaming program, which collects tweets as they are published in the time frame that the program is running. For this examination, the Twitter streaming API was used instead of the Firehose API. The Firehose, while a capable of scraping all tweets during a certain time period, is only possible through the proprietary service, Gnip, which is owned by Twitter. The streaming API was used instead and the code to pull similar tweets can be found as Figure 2 in Appendix B. It should be noted that the streaming methods used retrieved what can be considered a random sample of all tweets posted on the subject. The streaming API returns recently published tweets in no particular order and exclude tweets based on the capacity of the server to record and push them to the computer accessing the stream. Some analysts have estimated that the streaming API collects anywhere from 43% of queried content at best to as

low at 14% (Morstatter 2013). Additionally, the streaming API struggles to return more tweets during events when there is a sudden surge of tweets.

There were four nights where the amount of tweets published exceeded the capacity of Twitter to deliver all the tweets through the stream to the computer collecting them. These four nights were: 9/26, 10/4, 10/19 and 11/8. It is no coincidence that these were the nights of the debates (both Presidential and Vice Presidential) and the election night. These were also the nights that the stream was opened outside the regular times to capture event reactions. To compensate for this deficiency, these four dates were weighted according to the capacity reached. Figure 5 from the appendix displays the Morstatter evaluation that guided this weight and Figure 6 shows the linear equation used to downscale the data. Finally, the ratio between the tweets pulled during the rate limited nights and the average number of tweets pulled daily was used to adjust to the final points presented in this paper.

Outside of these rate limited nights, no other night returned any warnings of rate limiting and the total number of returned tweets additionally indicated that most nights probably returned nearly all, if not all, tweets posted during the time the stream was open. However, it is frankly impossible to be fully confident that tweets received by the API are entirely random without knowing the proprietary software and methods that define Twitter. It is very unlikely that content delivered through the API has a sentiment bias though. First it would require a separate and computing intensive process to detect the emotional sentiment of a tweet. This process would delay pushing the tweet via the API to the user (in this case this author). Even if there was a highly automated method of sentiment analysis like the one used in this paper, it would require additional time and sorting algorithms to choose which tweets to give to the users and which ones not to published. Seeing as the tweets referenced in this study have time codes near

milliseconds apart, it is safe to assume that there was no significant strictly bias filter applied to the tweets before pushing them to the user. This still leaves questions of if the meta-data associated with the tweets would be used for sorting. In other words, it could be possible that Twitter passed on disproportionately more popular, more geographically local or even simply shorter tweets to the user. The best refutation of this concern comes from the data itself. Adjusting for differences in daily popularity (debate nights were more popular than regular nights) and certain exogenous factors like interrupted streams from bad connections, most nights produced tweet sets with a similar allocation of popular, unpopular and locally distant users. To add another level of confidence to the sets, each was audited for popular user accounts that usually post in that time. Across all nights, accounts associated with the major news publications had their tweets appear in the set if they were posted at this time. While this does not mean that this study can be absolutely certain of a random sample, it can be assumed that major bias inducing factors are not present.

With these limitations in mind, this study looked to collect tweets every night over a period of two and a half hours. Each night from 7:15PM to 9:45PM, a stream was opened and tweets were collected about each major party candidate using key words relating to their names. This was the only layer of filtering that was used in this study and the precise filter can be found in Figure 2 of the appendix on the last line of the code. Slogans were avoided as these could include more positive results. Due to the fact that there was a different amount of tweets posted each night, each nightly tweet set was a different size. This presented a potential problem as comparing nights to each other would mean comparing busier nights with quieter ones and this difference alone could affect the sentiment of the tweets. To account for this, each night was examined both for the total number of tweets and each day's difference when compared to the

mean. This led to the understanding that any amount of negativity, no matter how it was operationalized, must be normalized so that a night with more activity could be reasonably compared to a night with less activity. This normalization is detailed more below in the Tone Scale equation.

Tweet sets, before being analyzed for sentiment, were cleaned for language and interpretability whereby other languages than English and tweets of identical content but posted by the same user (IE tweet spam) were removed. The ratio between the original "dirty set" and the eventual "cleaned set" helped to guide how best to normalize the different nights to each other. What was discovered was that even the smallest sets had similar ratio of dirty to clean as the higher capacity nights. This was interpreted to mean that all nights could be normalized by the same equations and compared to each other only with small consideration between sizes. It was finally reasoned in this experiment that as long as the stream was consistently opened and the internet connection not interfered with, that nights with a smaller amount of returned tweets were simply less active nights.

Separate to the nightly Stream API, a separate REST API was run. The REST API is a query that can return all tweets associated with a single user account. This request is limited to 3,200 previous tweets from an account and the rest API was run on both October 19 and November 15 to get as many tweets that were published in the observed time frame. These data sets for each candidate was then sorted and cleaned resulting in 2,884 tweets for Trump and 2,715 for Clinton in the time frame. The cleaned data sets were then examined and each tweet was sorted to indicate whether it contained negativity as defined by here. The author then used the coder instructions listed in the appendix as Figure 8 to establish consensus on which tweets from each candidate were negative. Among the five other coders, the highest accuracy achieved

for a single category was in Trump negativity at 87.5%. Clinton consensus numbers were lower at 81% but through discussion it was concluded that a plurality of miss categorized tweets could be understood to be informative or negative by calling out verbatim certain statements of her opponent. These "informative" tweets caused the most disagreement between coders but did not detract from consensus enough for this paper to not use this method to produce our independent variable. Other similar studies have, instead of using percent agreement, have instead analyzed expected agreement with observed to created kappa measurements. Due to this study only using considering two real categories of tweets (negative and non-negative), using the percent agreement method did not overly represent the agreement in the set as it would for sets with more categories. Additionally, in other studies with similar goals (Malloy and Pearson-Merkowitz 2016) (Thelwall 2010) (Friedrich 2014), a rating of around 90% for intercoder reliability has been readily accepted as sufficient. Now only two categories of tweets was utilized since both sides of the ongoing argument over the effects of political negativity agree that negative messages uniquely affect political communication over positive messages. By focusing on this type of political messaging and measuring its relative frequency compared to all other types of messages, this study hopes to isolate distinctly the affects of negativity. It is also logistically far more challenging when considering different categories of tweets. By adding new categories, this would only obfuscate the effects of negativity in exchange for information on tweet types far less interesting and important to the study of political communication.

Now to actually determine the sentiment of tweets, three different lexicons were used. Lexicons are are basically dictionaries of terms with corresponding numbers to rate negativity. Both Kramer and Robinson have utilized this approach to sentiment analysis as well as multiple articles published by the 538 blog. It is a far less sophisticated method of sentiment detection as

compared to monitored methods like machine learning. However, its frequent use by academics (Bing Liu 2012), bloggers (Robinson) and news publications (NYT Upshot) proves this method to not only be useful but widely accepted by multiple fields. Since this study was concerned with detecting negativity as a dummy variable, the magnitude (IE positive or negative) of each tweet was considered instead of the actual numbered value. In other words, a lexicon that rated a tweet as -4 for having multiple words with negative ratings would only show up in the data as being negative. More negative tweets were not considered more heavily or lightly compared to less negative tweets. Finally tweets that had an equal amount of positive and negative were rated as a neutral zero. It is possible that these neutral tweets could be considered covert negative but due to the analysis method were lost. However, audits of 0 ratings more often than not returned evidence that either a lexicon was not able to recognize misspelled words or slang and thus the quantity of covertly negative tweets is considered insignificant in the perspective of potentially larger lost data. The total amount of lost tweets is furthermore considered insignificant as the use of three different sentiment lexicons provided for greater coverage of the data sets.

In addition to a lexicon-based analysis, a machine learning approach was attempted. While these results will not be discussed since the capacity of this project was not able to produce an accurate enough algorithm, the effort and insight from this part of the project is still worth small discussion. This process was likely to create more accurate results but proved to more labor intensive. It was estimated that to achieve high levels of accuracy in the algorithm (nearly 80-90%) that a vast majority of the nearly 60% of the total 10 million tweets collected would have to be hand coded. These hand coded "testing sets" would inform a Naïve-Bayes algorithm which will attempt to sort based on rules the computer would observe from a hand coded set. One such rule could be identifying all words that the candidates use more often than

others for a specific sentiment. The Naïve-Bayes and other machine-learning algorithm work by identifying concordant pairs: or pieces of information that share a common characteristic. This study attempted to identify these data points through coding multiple test sets of 2,000 tweets to little success. The test sets were coded through projects posted to Amazon's Mechanical Turk and then audited by the author for accuracy. While the human coders achieved a high level of accuracy, this could not be easily translated over in black-box machine learning algorithms.

The observed machine learning route, while useful for its ability to automatically code large data sets dynamically, required a massive amount of hand coding. Even if a large portion of the tweets were able to be hand coded and properly made into testing sets for the machine, there would still be several high level linguistic concepts that would be near impossible to train for like sarcasm and puns. To solve this problem, a less nuanced and slightly limiting view of contagion theory should be taken. Instead of tracing word patterns endemic only to our data set, the general lexicons discussed were used.

The lexicon-based approached also faced a challenge to accurately code for sarcasm and other high-level language but it might have providence in its weakness. While the machine learning algorithm might correctly identify sarcasm a few times out of many, the lexicon based approach will fail every time, consistently. If we are considering users quickly encountering messages and using this to either consciously or unconsciously shape the sentiment of their future messages, it can be argued that irony and high level language patterns might be lost occasionally on the general user[1]. Thus the lexicon fails consistently like a human would in the same circumstance. While not ideal, this method should be understood in the context of the other

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[1] This phenomena is also supported by "Poe's Law" which states that comments online that are overly sarcastic or facetious, without clear indications that they are ironic, cannot be relied on to be accurately identified as such without clear signals of the authors intention. In other words, overly sarcastic opinions stated extremely have a tendency to be interpreted incorrectly without sincere indicators

options available. Coding and automatically accounting for sentiment is an extremely difficult and is right now the cutting edge of machine learning and nature language processing (Emspak). Instead of attempting to solve a far larger problem than the scope of this study, it was best to accept a degree of inaccuracy in the lexicon method in exchange for its ability to consistently return relevant data for this study.

Using the lexicon based approach, non-English and tweets and repeats from the same account were then filtered out to come to final count of 5,289,845 tweets collected from the Clinton stream and 7,812,551 tweets from the Trump stream. This number was collected from between September 26th and November 8th but out of the 45 total dates that data was collected, only 38 produced usable data. On several nights, data was inconsistent or impossible to retrieve due to internet connectivity issues (9/27, 9/29, 10/1, 10/22). On several more nights, a hardware issue prevented collecting data (10/10-10/12). With a collective week missing from the data, and due to the dispersed nature of the missing nights, it is hard to estimate how much data is missing. Thankfully all debates were captured and the election night was well documented. After collecting the data, the tweets were cleaned by removing syntax and considering frequent negating bigrams. This can be found in the Figure 7 of the appendix and the Tweepy and Twitter, R packages were also used once the translated CSV's were uploaded for final analysis. When the lexicon referencing code applied the final sentiment numbers, the range, as stated previously was simplified to only positive and negative. This study is only interested in the prevalence of negativity, not the intensity so each corresponding number was then translated to its absolute value and all tweets in a negative range were assigned a value of 1 for negativity present and all other tweets were given a 0 for negativity not present. The total number of each type of tweet, negative and non-negative, were then counted and he following equation was then used to

describe a single point of data representing the tone scale of a single day's worth of Twitter messages:

Tone Scale$_{cd}$ = (non-negative message$_{cd}$ – negative message$_{cd}$) / (non-negative message$_{cd}$ + negative message$_{cd}$)

The Tone Scale equation measured the amount of non-negative messages by a certain publisher (c) per a certain day (d) minus the negative messages. This is then divided by the sum of the two numbers to create a scale for the day. As stated earlier, the two categories for tweets to be sorted in were simply those with more negative scoring words than positive and those with more positively scoring words than negative. Because a tweet with more positive words than negative is not inherently positive (IE they could be informative, non-relevant or neutral), the best way to categorize this set is simply as being not negative IE non-negative.

Each lexicon produced different tone scales even though a search through their strings indicated that most contained similar words. Deviation from one to another can be explained in how each one distributes weights and considers language. For example, the same word in the Bing Liu lexicon could be given a different weight in the MPQA and if there was a positive word of a different quantity, each lexicon could possibly return a negative number while the other counted as a non-negative total.

For this analysis the MPQA, Bing Liu, and the Harvard Inquirer lexicons were used. Figure 9 in the appendix provides a more in depth consideration of these lexicons. It should be noted though that there were more customized Twitter lexicons that could have been used but were not due to resources and time. The three lexicons that were used are considered general lexicons though some like the Bing Liu have been utilized to analyze smaller sized text samples. Each of these lexicons is also closely associated with academia with the MPQA coming out of the University of Pittsburg, Bing Liu from the University of Chicago, and the Harvard Inquirer

from the college of the same name. It should be noted all of these lexicons had issues interpreting emogees. These symbols have only recently been added to Unicode and thus different applications approach UTF-8 errors differently and thus could contribute to the disparities in the negativity Tone Scales. Interpreting these characters could be in itself an entirely different effort and there are multiple scholars that have attempted to do so (Kabir 2016) (Zhou 2014).

Data

Insert Figures 1 and 3 Here

The first aspect of the data to note can be found in Figure 1 and Figure 3 of the appendix. These histograms describe the dispersion of negativity as expressed by the major party candidates. These were the independent variables for this study and almost immediately a difference in campaign strategy can be seen in each. First, it appears that Clinton was generally more positive and this can be seen with her most frequent sentiment days, which were around the .5 mark on the Tone Scale. Recalling the Tone Scale and how it is calculated, this means that for more than a week throughout the campaign, Clinton's Twitter account tweeted 50% more non-negative tweets, than negative when compared to the total tweets for the day. In other words, of the 25 tweets published that day, 19 were coded to be non-negative compared to 6 coded negative. This aspect of the tone scale means that higher numbers on either end of the spectrum should be considered with the additional weight that they carry. A number closer to zero would indicate a neutral day, or a day where the amount of non-negative tweets were equal to negative tweets thus making the percent of total difference to be close to zero. Knowing this and returning to Figure 3 and 1, it can be seen that Trump's most frequent type of day was in just below neutral zero indicating a solid week throughout the campaign where the @therealdonaldtrump was producing around 10-15% more negative tweets when compared to the total tweets for the day.

It is additionally notable that Trump's second most frequent types of days were very negative at the -.5 mark and very positive at the 1.0 mark. This means that for 6 days throughout the campaign, Trump's Twitter was very negative (-.5) or near entirely positive with a few days garnering a 1.0 rating meaning that every tweet published was positive. However, this does not mean that Trump was the more positive candidate. The mean negativity for each candidate throughout the campaign was .3158 for Clinton and .1963 for Trump. While both were on average not negative, Trump had a greater quantity of days that were both negative and very negative drawing his average sharply downwards. This is reinforced by the extremes of both candidates since the most negative day for Clinton's account was -.52 while Trump, on October 28th, produced a tone scale of -.82.

Insert Figures 2 and 4 Here

With this knowledge of the independent variables, it is appropriate to begin to discuss the dynamics of the dependent variables, which is the negativity of Twitter users towards the major party candidates. It should be noted that Figure 2 and 4 represent the calculated negativity of each night using the three lexicons discussed. The average of the MPQA, Harvard Inquirer and Bing Liu were used to assign nightly Tone Scales based on the tweets published by general users. An initial look at these figures show a stark difference in how Twitter discussed the candidates in the time that the stream was open to collect tweets each night. At just a cursory look it is easy to tell that Trump seemed to enjoy more positive nights than Clinton with Figure 4 showing the data mostly centered around the .2 Tone Scale rating. Clinton, by comparison in Figure 2, had the greatest number of days around the -.2 Tone Scale rating. Before delving into the differences between the candidates, it should be noted that the range of the dependent variable is reduced when compared to the independent variable just discussed. This can be easily

explained by the differences in capacity for each variable. While one Twitter account, even if a social media addict runs it, cannot compare to the stream of Twitter information collected for even the small amount of time per night done in this study. When collecting tweets on several orders of magnitude greater than another set, it is understandable that it would be harder to achieve higher Tone Scale values on either side of zero.

Returning to the data at hand, it can be seen that the initial look at the histograms is reinforced by the raw statistics. Clinton had a mean Tone Scale of -.02193 while Trump enjoyed a .008946. While enjoying a Tone Scale rating close to zero, Trump still had worse days than Clinton. Specifically, Trump received a -.63 Tone Scale rating on October 19th while Clinton's lowest point was the same day at -.45. Recalling back to the amount of data collected by each candidate, it is useful to consider that since Trump was simply more popular on Twitter (in the terms that there were more tweets collected about him than Clinton) that his range could be due to his popularity. What is additionally interesting about both these figures is that both candidates suffered from a negative slump. There were a handful of days that both candidates received Tone Scale ratings that were significantly more negative when compared to the next most negative days. A close look at these days reveal that the most negative days occurred on critical campaign nights like the first and last debates. This supports an understanding of this data as partially dictated by events outside the control of the candidates. This study is concerned with the effects the candidates could potentially have on each other and thus understanding the spurious factors that could supersede this influence is invaluable when considering this data.

Before analyzing this data for the interactions predicted in the hypotheses, a small comparison can be made between the independent variable histograms and the dependent ones. Comparing Figure 1 to 2 and 3 to 4, it appears that there is an interaction between the sentiment

of the candidate's tweets and how the greater tweeting public considered their opponents. Trump's generally lower average Tone Scale seems to be reflected in how, on average, other users seem to report a lower daily Tone Scale of Clinton. By comparison, Clinton's positivity seems to be reflected in how Twitter considered Trump on a daily basis with both Figures 3 and 4 showing a right-hand skew towards more days with increased non-negativity. However, this is as far as this study can go without investigating the correlation between the variables. It should be emphasized that this data was time dependent as each point of data represented a day's worth of tweets. It has already been briefly mentioned that the relationships between these data points could have been separated by time and the days that Clinton was producing tweets in far higher non-negative amounts might not have happened anywhere close to the days that Trump enjoyed less negativity from the Twittersphere.

Analysis

Investigating H(0): Null Hypothesis

To investigate the relationship between the variables, analysis should start with a description of each candidate's negativity over time. This can be observed in Figure 5 and 6 where the negativity expressed by each candidate's account is projected over a timeline of the campaign. As mentioned in the Research Design, there were multiple days where data could not be collected and thus several dates are missing on this timeline that starts at September 26th at 1 on the x-axis and ends on November 9th at the far right hand side of the same axis. Day 10 represented the October 8th, Day 20 October 21st and finally Day 30 contains information for November 1st. With this understanding, a pattern emerges in the tweeting activity of @hillaryclinton and @therealdonaldtrump. Both candidates seem to have become far less negative in the final days of the campaign which contradicts an early observation made by

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Simendinger that was mentioned in the introduction. It seems while the traditional messaging mechanisms of the campaign went negative in the final days; the Twitter accounts of both candidates went for a more positive sprint towards the end. When the individual tweets are considered from this time, there is a larger quantity of tweets encouraging people to vote and to attend rally and campaign events. This is one of the first observations that show a divergence between the reported traditional strategy and the realized end of campaign tactics used on social media.

Insert Figures 5 and 6 Here

Additionally, both candidates' seem to have adopted a similar strategy near Day 20 of the study, which coincided closely with the last debate, scheduled on October 19th. Clinton's account reaches a peak around the days before the debate then slip into a negative valley that lasted until Day 30. Trump, on the other hand bottomed out slightly sooner but as on a more consistent attack pattern having become more negative since the beginning of when the study was conducted. This supports a more event-oriented theory of campaign activity and leads a small amount of credence to the null hypothesis. Other studies have found similar results when considering key media events. One such study was done on the 2012zz French Presidential campaign using the same streaming API tool utilized in this study (Wegrzyn-Wolska). However, the second that the dependent variable is considered along side the independent, there mounts sizable evidence that there is at least some type of interaction between the variables listed in this study. Directing attention to Figure 7 and 8, the negativity expressed across Twitter towards the candidates can be seen in the same time scale.

Insert Figures 7 and 8 Here

Both the Opinion of Clinton and the Opinion of Trump, expressed across the time of the study, show the tell-tale bump at around Day 20. This is the point that the campaign Twitter accounts became relatively more negative and Clinton and Trump discussed each other more negatively. It should be noted again that the change in sentiment for the greater tweeting population is significantly less than the change from the candidates' accounts. This is because tens to hundreds of thousands of tweets inform a single point in Figure 5 and 6 while 7 and 8 are informed by at most 90 tweets. The fact that in both of these sets of figures there exists a negative slide towards the final debate could be interpreted to mean that events drive Twitter activity more than anything else. However, this does not consider all parts of the graphs discussed. It should be noted that Trump enjoyed a upward trend up until around the 15th day of the study which moves closely with the initial tweeting patterns of the @hillaryclinton account over the same period of time. Additionally, at both the start of the study and at the end of the study, when Trump seemed to be tweeting negatively the least, clusters of data aggregate below the smooth ab-line displayed in Figure 7. Both of these observations hint that the candidates and their Twitter activity could be affecting how others tweet about their opponents at all times during the study, and not just around major debate nights or campaign events.

To finally reject the null hypothesis, the contents of Table 1 and 2 can be referenced. These tables show how the sentiments of the candidates' accounts correlated to the sentiment expressed by the greater Twittersphere. Additionally each independent variable was divided into three distinct categories of Positive, Negative and Neutral. These categories were bound between +1 to +.05, +.05 to -.05 and -.05 to -1 respectively. These segments represent what this study considered Positive Days, Neutral Days and Negative days worth of Twitter activity. The Neutral category was the most constrained as these days were considered to have a special effect on the

data analyzed. They represented the instances when there was a near equal amount (only 5% more as compared to the total amount of published tweets) of both negative and non-negative tweets. Knowing that each data point could represent several hundred thousand tweets, this narrow window is appropriate to capture a rare campaign instance when there were generally equal amounts of negativity and non-negativity detected. Considering these divisions and the interaction of the full independent variables, the null hypothesis can be rejected when specifically citing the interaction between the three different levels of Trump sentiment (represented as tsb in Table 2) and their interaction with the aggregate sentiment of tweets about Clinton derived from the lexicons (represented as c.ag.sent in Table 2).

In this example, there is some of the highest statistical significance with incredibly low P-values and robust estimated interactions (represented by B). Both the negative category and the positive category of Trump's tweets have a 99% confidence in their statistical significance and a confidence interval that closely relates to the section of the data expected. This level of statistical significance instantly discounts serious consideration that the data collected are not in some way correlated. However, this is only for the effect that is expected at multiple different levels of Trump tweets on how Twitter considered Clinton. When the opposite is considered in Table 1, there is a less clear interaction. Looking at the Clinton levels (or csb) in Table 1, it appears that the distribution of points in the regression is far too large to be considered statistically significant. Additionally, when comparing the Clinton account sentiment levels to the Trump account sentiment levels, there is a clear difference in model fit with the Clinton levels in Table 1 only having an R-squared value of .168 while the Trump levels in Table 2 are nearly double.

However, there is still a degree of statistical significance to be found in Table 1 when attempting to explore Clinton's potential effects on how Twitter users mentioned her opponent.

The independent variable listed as clinton.sent is the unbroken continuous variable describing Clinton's account's sentiment throughout the entire campaign and looking at its correlation to the changes in the aggregated sentiment towards Trump, there emerges a single degree of statistical significance found in the bottom right corner of Table 1. The lower P-values indicate a sizable competency in this model's ability to also describe some of the more extreme points of data and the higher R-squared values also shows a better overall fit to the data described.

Simply from data fit statistics it can be determined that both Donald Trump and Hillary Clinton's tweets correlated to changes in how the greater Twitter audience discussed them. While this resolutely disproved that this data is random, or entirely event driven, the differences in these correlations bring up additional questions. For instance, why does Trump's sentiment only correlate when divided into three separate categories? Additionally, why doesn't Clinton's sentiment correlate when divided into the same distinct levels? These questions lead to the next subsection of these results, which will entertain the individual hypotheses postulated about this data.

Investigating H(1): Corrective Action

To address the questions posed in the last subsection, one can look back at the tables discussed with renewed focus on the B value, which represents the estimated deviation. Now it is important to remember that this statistic measures a 1-unit movement along the independent variable and projects the change in the dependent. Because this study considered all variables along a spectrum of -1 to +1, the estimates represented in the tables show what the estimated value would be for the dependent variable given a completely non-negative day in the independent since a full +1 on the Tone Scale represents a day when the difference between non-negative and negative represent 100% of the total amount of tweets for that day. Knowing this, to

address the theory of corrective action, one can look to the comparative explanation and fit of both the Trump and Clinton daily sentiment when compared to how the greater Twittersphere tweeted about them.

It was also hypothesized that Clinton would be the target of "corrective action" where her own rates of negativity would correlate to larger negativity directed at her. This is also a comparative hypothesis, which states that Clinton's effect on herself would be stronger than Trump's effect. Looking at Table 2, which charts sentiment towards Clinton for all independent variables, the opposite can actually be found. The lower right of this table shows a firm zero for the B column that indicates no effect whatsoever. Also, an extremely large P value indicates that the Clinton effect on Clinton model has extreme difficulty tracking most values. The low R-squared values also indicate that the model has a difficulty with describing most points in its set. However, this observation is caveated by the fact that it seems that Trump was also not able to correlate fully along this set of information. With half the P-value but only a B value of .05, it seems like for the data described in this model, that neither candidate had much of a correlation to how negatively Clinton was discussed.

Insert Figures 11 and 12 Here

Yet, if one recalls back to the segmented Clinton and Trump sentiment variables, it seemed that when Trump is segmented, all levels reach a very high degree of statistical significance. The Clinton levels in the center of Table 2 create a better fitting model but one that is still woefully incapable of reaching the same level of competence as the Trump levels. It does appear however that the biggest improvement on fit for the Clinton levels happens for the negative and positive tiers with each having a B value of -.13 and .14. This means that if each ab-line for these subsections of the data were plotted out to a theoretically completely positive day

(+1 Tone Scale Value) that the negative day would return 13% more of the total tweets to be negative than non-negative. Conversely, if plotted out from the positive subset, Clinton would receive 14% more of the total tweets to be non-negative.

This observation establishes our baseline for how Clinton's own tweets could affect how negatively other Twitter users tweet about her. Though the rest of the statistics prevent this from being statistically significant, for the sake of exploring this hypothesis, this baseline is essential. Before comparing the Clinton effect on how she is discussed on Twitter to the Trump effect, it is important to visualize the data discussed. In Figure 11 and 12 we see the information that was just expressed numerically and several things quickly become apparent. First, it seems that there are three defined subsets in Figure 12 that show there is a grouping of Tone Scale days below the abline but to the left of the zero, below the abline but right of the .5 mark and finally a cloud of points above the abline but sequestered between 0 and .5. This shows the bend upwards in sentiment when Trump was more neutral (IE had a more equal number of non-negative and negative tweets) and a dive back down when Trump is either positive or negative. This explains why when the data is considered on a whole, the model makes a poor fit as is reported in the lower right section of Table 2. It also shows why when the Trump independent variable is divided into the three cohorts, the new segmented variable describes the data far better. This is a very strong indicator that Twitter users respond more strongly along the subgroups cut from this data set.

More interesting is that this observation creates ample evidence refuting the "corrective action" hypothesis. Both graphically and statistically, Trump had a stronger effect on how Clinton was discussed on Twitter than Clinton had on herself. Not only are Trump's statistics far more robust but also the B values are significantly larger. Specifically, when considering the

positive cohort for Trump in Table 2, the B value is .23 and the neutral is .36 while the negative is -.18. What these numbers actually measure is the amount difference between cohort when compared to the negative tone scale cohort. Thus when looking at the neutral number of .36, that must be first compared to the -.18 for the negative category before finding the projected mean of that day. Therefore, when considering days when Trump was more neutral versus the days he was more non-negative, it seems that the average would be .05 tone scale and .18 positive days and neutral days respectively. This is interpreted to mean that when Trump is more neutral, or has more days with equal amounts non-negative and negative, that those days correlate with higher rates of non-negativity towards Clinton. Thinking more on this and looking at Figures 12 and 11 specifically, this opens up a very frightening possibility: chiefly that Trump is able to provoke negativity in Twitter even when he has more positive days. In fact, this observation would indicate that it would be best for Trump to dedicate his Twitter account to negativity or non-negativity entirely to prevent any amount of non-negative tweets to be posted about his opponent.

This relationship and its implications will be explored in more detail later in this study, but there still is more work to be done understanding "corrective action" in this context. If Clinton is not the target of this type of phenomena, could Trump? It could very well be that Twitter can be considered its own autonomous platform where the mainstream candidate is less dictated by mainstream authorities, party figures or opinion leaders, but instead by the masses participating in the Twittersphere. To test this variation of the hypothesis, attention should be directed back to Table 1 and specifically at the lower right. It seems that both the independent variables for Trump and Clinton's Twitter activity have significantly small P-values and encouraging B values. With one point of statistical significance each, it can be understood that

both Clinton and Trump had an effect on how Trump was tweeted about. This can be seen with the similar graphs shown in Figure 13 and 14.

<center>**Insert Figures 13 and 14 Here**</center>

Both of these figures have a generally positive slope that cross the zero neutral point on the x-axis at around the same point. Referencing back to Table 1, it seems that the ab-line for Figure 13 describing Clinton's effect has a steeper slope and reaches further down on the y-axis than the Trump line in Figure 14. It also seems that there are fewer outlier points in Figure 14 that pull parts of the adjusted ab-lines down further. This makes it difficult to fully corroborate presence of "corrective action" towards Trump but a stronger case is made for this candidate when compared to Clinton. It seems that both Trump and Clinton affect how Trump is discussed on Twitter, but Clinton enjoys a very slight edge at provoking negativity towards her opponent.

It would seem then that this hypothesis does not apply to Clinton and while more descriptive of Trump, the graphs and data does not support a conclusion with an acceptable degree of confidence. It is however note worthy that if any interaction had been found for this investigation, it would have been towards Trump. This indicates that Twitter operates differently in creating mainstream candidates that would be affected by "corrective action". To a degree, this makes sense for this analysis. Trump has held a Twitter account for longer than Clinton, has had more followers for longer and also was noted to have more control over his social media account. It is premature to call him the "mainstream Twitter candidate" but the strength of his model over Clinton's to describe negativity towards himself hints that with more precise study, it could be argued that he was the victim of "corrective action".

Investigating H(2): Spill Over Cycle

Unlike previous theories, the "spill over" cycle is fairly hard to prove and due to the differences in how many tweets describe the independent and dependent variable, it can generally be asserted that the Twittersphere never was able to reach the same Tone Scale of negativity as either candidate did. This does not mean that this theory is not worth investigating and the first way to investigate if negativity displayed stubborn dynamics is to look at the opinion time scales represented in Figure 7 and 8. Now if there were to be stubborn negativity effects that would not change even with a positive candidate, then it would be expected in these graphs to see fairly few positive and very positive dates next to negative ones. This is not the case in either chart. Both Figure 7 and Figure 8 have very low nights right next to some of the higher nights. "Spill over" theory states that this could not happen unless the candidates themselves were extremely positive to account for these.

Insert Figures 15 and 16 Here

This is not enough to reject "spill over" as a theory entirely. It should be remembered that this theory comes from a previous study that looked at how negative television advertisements correlated to increased negativity in the online comment section for newspapers. Adapting this theory meant considering the candidates as more dominant actors in Twitter (IE making them the television ads) and considering Twitter users to be more like TV viewers that would re-express the sentiment that they take from the candidates and regurgitate it back onto the platform. This is why this theory, for this paper, included the word "cycle" to indicate how endogenous the feedback would be in the same system.

Therefore, to explore this theory further it seems appropriate to reverse the causal arrows to instead describe the situation of the candidates being informed by the Twitter comments. Now this reversal is partly due diligence to understand the data and partly to explore if the candidates

saw "spill over effects" from the Twitter environment. Before exploring this possibility, some caution should be measured for the results. It would be practically impossible for this connection to happen logically as the stream that was used to collect the dependent variable of the Twittersphere's sentiment of the candidates, was only opened for a specific period of time each night. If statistical significance with strong confidence is found, it is difficult to argue that the candidates still were affected by how the rest of Twitter was tweeting about their opponents. Tweets published by the candidates' accounts happen at all times of the day and also could have been published by the candidate themselves or by their media teams.

It is additionally hard to argue that the sample collected nightly is representative of the rest of the day. This time was selected intentionally to mimic how average Twitter users consume their media and then respond to the sentiment they received. However, it is still helpful to explore the possibility that to at least some extent, that the social media environment might have impacted the candidates.

Looking at the models by Figure 15 and 16, there might be some credence to the theory of "spill over cycles". But this is expressed different for each candidate. In Figure 16, it seems that when Twitter is more negative towards Clinton, there are both a cloud of positive Trump days and Negative Trump days. Meaning that when Twitter is more negative towards Clinton, Trump fluctuates on how much he attacks her. As Twitter warms up to the democratic nominee, it would seem that Trump backs off from both ends of the spectrum resolving instead to be more neutral towards the candidate. This is different for Figure 15 where it seems that when Twitter starts to be more positive towards Trump, Clinton backs off of attacks and is instead more positive.

These results are not only contradictory but confusing. If the causal arrow was able to be reserved, and the candidates took notes from the greater negativity expressed around them, then one would expect the candidates to go more on the offensive when it seems like Twitter is warming up to their opponents. This not only contradicts extant negativity theory outside social media, but also seems to cut down the "spill over" theory even further.

Investigating H(3): Contagious Effects

With the analysis so far, it seems that some theories are more relevant and applicable than others. However the final theory to explore might actually be the best explanation for the phenomena explored in this study. This theory basically pits the independent variables against the dependent and predicts that the while there will be strong correlation for days that each candidate is negative, this effect might not be fully realized on the days with a higher Tone Scale. This theory draws most directly from the Kramer study mentioned in the literature review that looked to invasively change the content users received to check their changes in sentiment. In this study, instead of changing the feeds of Twitter users, it was predicted that the candidates themselves, and the surrogates that would be directed by them, would serve as the changes in presented sentiment to the users.

Knowing this, it would be expected for Figures like 12 and 13 to show specific patterns. Primarily, one would expect that these regressions would have tight prediction lines when the candidates produced negative content and would disperse or deviate as the candidates got more positive. This is seen best in Figure 12 and confirmed by Table 2 when looking at the top left. This part of the Table shows that there is a very high degree of statistical significance when only considering the days that Trump went negative. The corresponding part of the graph shows that not only is there a downward trend as Trump went more negative, but also that a majority of the

points fit into the model. This observation has already been tangentially made in the exploration of previous theories but the robustness of the statistics that support it, from the high R-squared that shows a large amount of the data fitting, to the low P-value indicating a capability of the model to incorporate even the most desperate points, make this a concrete revelation from this study.

When comparing this trend in the Trump effect on tweets about Clinton, to the corresponding trend in the Clinton effects on tweets about Trump, the results are also interesting but far less compelling. Not only are Clinton's projected effects, as expressed by the B values, smaller, but the statistics that would lead to greater confidence seem significantly lower as well. For example, when Trump has a day that can be sorted into the negative category, the projected effect on Tweets about Clinton is -.18. The corresponding value for Clinton is less at -.13. The same trend follows for all levels of each candidate with Trump having more days corresponding with higher values for Tweets about Clinton and Clinton having lower effective B values for Trump.

Insert Figures 9 and 10 here

When visualized into boxplots in Figures 9 and 10, this interaction becomes most apparent. Moving from right to left on Figure 9, it can be seen that when Trump attacks Clinton, IE his Tone Scale falls into the negative day category, Clinton receives the worst days in terms of the negativity received. The mean of these days is around -.19 while when Clinton has similar attack type days for her opponent, Trump actually enjoyed higher mean Tone Scale than the days that Clinton is more positive and net neutral. It should be noted that the whiskers on both Figure 9 and 10 are particularly long for the negative days showing a large range in the corresponding greater Twitter negativity for those days. Neutral days, for both sides are more clustered towards

their mean which makes sense once given the context that these box charts represent only from -.05 to +.05.

One of the most interesting finding from this set is the one mentioned earlier, chiefly that when Trump is positive, he still elicits a lower mean Tone Scale score than when he is neutral. The implications of this are profound for any candidate that can affectively "go negative" without actually sending out negative messages, is a potent force in politics. For this election cycle in particular, it might have been both a mixture of Trump and Clinton as candidates. It could very well be that the only case where one candidate could elicit negativity without being negative is if their opponent was already operating in a communication platform and potentially hostile to them. From the findings in the previous section that suggest that Trump could have a higher likelihood of being the "mainstream Twitter candidate" ripe for "corrective action", it would mean, by implication, that Clinton was the "outsider Twitter candidate" that was already in hostile territory engaging online.

Furthermore, contagious effects show that each candidate is more effective at eliciting negativity targeting their opponent than any candidate could provoke towards themself. In other words, in the social media sphere, and accounting for contagious effects, a candidate is more at the mercy of their opponent and the Twittersphere than they might be normally. It would be impossible to state this definitively from this study alone since to prove this, one would have to compare negative effects outside the social media sphere. However, the indications from the segmented independent variables show that not only is negativity contagious, but each candidate play a central role in directing the vitriol that the other receives.

Conclusion and Further Study

For all the confidence in the models found in this study and the compelling results derived, there is a large amount of room for improvement if additional iterations of this research are to be conducted. First, the coding used could be streamlined to give results of Tone Scale on a nightly basis instead of first collecting all of the raw JSON data and then parsing it into insights later. Secondly, there is much room to innovate with more precise lexicons and the potential of some machine-learning methods to achieve a degree of extremely high confidence in even complex language concepts like sarcasm. Finally, the meta data of Twitter accounts and tweets could be further utilized to make models more considerate of advanced features of social media.

However, making this study better for future iterations should not detracts from the compelling findings made. It seems like there is not only an interaction between how negative the candidates tweet about each other and how negatively the rest of Twitter discusses them, but also it seems like this interaction is very strong. The null hypothesis was very to disprove which opened up the interesting opportunity to explore the interaction between the independent and dependent variables further. What was found when each hypothesis was challenged was a degree of agreement with extant theory, and additional insights about the specific environment of social media.

The least conclusive hypothesis was that of "corrective action" which was found to actually not be as applicable to Clinton as first suspected. When reversing the theory to assume Trump as the "mainstream Twitter candidate" the theory proposed offered additional insight but could not be conclusively supported. This is chiefly because "corrective action" stipulates that the subject of the attack is more affective at provoking negativity than their opponent and with Clinton equally to marginally more effective at impacting sentiment towards Trump, it seems that while "corrective action" can guide an understanding of online negativity, it cannot actually

provide as much insight as other theories. Additionally, the neutral bumps seen in both Figures 11 and 12 seem to indicate both that negativity impacts users differently than other sentiments and that these effects are dulled the weaker they get. This may certainly not be a revelatory finding, but its support for previous understandings and their applicability to social media is sizable.

Continuing onto the next hypothesis, it seems that Spill Over, at least as described and articulated in this paper, is not a descriptive explanation to the phenomena observed. In fact, it was shown in multiple figures that the type of interaction predicted was concretely not there. A possible explanation offered previously was that the event driven nature of campaigns dulled these effects by making the day-to-day Tone Scale fluctuate more. When the original context of this theory was reevaluated and suggested that this study test the reserve effects of the independent variables to the dependent variables, it was also found not to have persuasive significance. While statistical significance was found in Table 3 and 4, the findings simply do not logically explain how candidates compose tweets and understand their place in the greater Twittersphere. In this sense it is better to consider the candidates as "opinion leaders" as is suggested by the two-step and multi-step flow models.

Additionally, just because this theory does not apply well to the data presented, or explain phenomena as well as the other theories suggests, it does not mean that exploring this wasn't critical to understanding this study. By knowing that the effects of negativity do not form into a "spill over cycle" from candidates to the Twittersphere and vice-versa, it can be reasonably assumed that there is little communicability between days. In other words, the sentiment of one day in the dependent variable does not impact the sentiment in the next day. This is a very helpful finding since if indicated otherwise, there would be concern of the dependent variable

affecting itself and obfuscating the effects that were predicted from the independent variable. A final explanation of this lack of interaction could be the event driven nature of campaigns discussed earlier. If there were any dependent-to-dependent effects, they could be washed away by the daily details, scandals and turbulence of the campaign trail.

The final theory entertained was the most convincing and explanatory. Not only did it give context and meaning to the high degrees of statistical significance in some points of the data, it also explained why points not described by the same models might not fit as well. The primary weakness of contagion theory is that it offers very little explanatory mechanisms as to exactly why sentiment is spread. As stated in the literature review, contagion theory is more of a collection of observations than a vigorous and full theory that can explain phenomena across mediums and time. For its weaknesses though, combined with the understanding of "corrective action" several strong conclusions can be rendered about the data explored and the results derived.

These conclusions are:

1) candidates have a greater impact over how each other are viewed than how they can impact how they are viewed

2) negativity operates differently than non-negativity and the effects are dulled the less negative one is and

3) a mixture of positive and negative in equal amounts creates results that are not just a continuation of the dulling of positive effects and negative effects

The best graphic by far that illustrates this is Figure 9 and 10 which show how the categories of sentiment for each candidate fluctuate on their affected mean. For both Clinton and Trump, their neutral categories do not fit into straight lines between the positive and negative. It

has already been discussed that the number of neutral nights might very well contribute to this, but the revelations brought from each are still important. At this point, it seems that not only is contagion theory an incredibly descriptive frame to understand negativity, but with support from studies like Kramer and Malloy and Pearson-Merkowitz, it seems almost impossible to discredit this affective mechanism of how negativity spreads online.

After collecting over 10 million tweets and processing, analyzing and arranging them into 38 distinct points of data, this study has revealed a stunning new potential for political candidates that see their races shift to the sphere of social media. Not only are candidates now given a hyper-speed and cheap information delivery system, but they can seemingly defy the odds and break prevailing assumptions in how campaigns work. The implications of this could be a more chaotic and vitriolic campaign setting edged forward by the possibilities that social media provides. It could also lead to an advanced form of political gamesmanship where the constant flow of events compete with the ability of candidates to broadcast their messages further than before. If the neutral bumps discussed and identified in this paper are real, social media could serve as a polarizing force. If candidates first understand that switching to attack and defense in the same day over a handful of tweets is the social media equivalent of "going off message" candidates might fully dedicate their Twitter feeds to promoting clear-cut positive messages and straight out brutal attacks. This is supported by the already discussed phenomena in the Trump data that shows that the candidate was actually able to provoke more negativity even in positive days, than he was for days with an equal mixture of positive and negative. The discussed figures and graphs would indicate that the most effect way to sway how Twitter users discuss your opponent is to take a stance, even if it is a positive one. However, this finding should be heavily

caveated by the observation that Donald Trump is no ordinary politician and his social media use is a feat in itself to replicate.

Regardless of if these effects are completely candidate contingent, there is ample evidence that social media will only become more relevant to campaigns as the 21st century turns on. From this study it seems that it would be best for any candidate to craft a social media presence that from the day to day sticks a particular stance whether it be a constant onslaught of negative messages or a consistently positive of informative stream of 140 character messages. Social media presents a new and exciting field in political communication and the eccentricities, dynamics and natural laws that dictate interaction across this medium will only be better defined by more observation and a diligent consideration of all factors that create this new world. Hopefully the findings here can serve as a basis for further study and critical though on just how do messages, thoughts and emotions spread and effect users in this increasingly connected universe of information.

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