EXPLORING THE COMMUNICATIVE AND ATTITUDINAL COVARIATES OF VIOLENT AND NON-VIOLENT POLITICAL ENGAGEMENT

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The undersigned, appointed by the dean of the Graduate School,

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EXPLORING THE COMMUNICATIVE AND ATTITUDINAL COVARIATES OF VIOLENT AND NON-VIOLENT POLITICAL ENGAGEMENT

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ACADEMIC ABSTRACT

This project is primarily concerned with the relationships between communication behaviors, including pro-attitudinal media use and political social media use, political attitudes, including in-group bias and political trust, and political behaviors, including both violent and non-violent political engagement. Political violence is defined broadly, including both communicative and verbal political violence factors, and a new measure of political violence is designed and validated using psychometric methods. A novel data collection and analysis plan is utilized to collect social media posts authored by participants in order to link indicators of social media content with data collected via a self-report survey. The results show that pro-attitudinal media use is related to higher levels of in-group bias and lower levels of political trust. Further, higher levels of bias are associated with non-violent political engagement and lower levels of political trust are associated with violent political engagement. The collected data revealed indirect effects between pro-attitudinal media use and both non-violent and violent political engagement through in-group bias and political trust respectively. To conclude, I situate these results within the research literature and outline future research that can further elaborate on these relationships, establish further evidence of the validity of the political violence scale, and refine and improve the social data collection plan.

Chapter 1: Introduction

Prominent academics have voiced concern that political violence may soon increasingly erupt within the United States due to political radicalization and polarization (e.g. Abramowitz, 2010; Iyengar, Sood, & Lelkes, 2012; Sunstein, 2009). The U.S. Department of Homeland Security has also warned that domestic terrorism is a threat to the national security of the United States (Perez & Bruer, 2015). A glance at news headlines shows numerous examples of political violence occurring in the United States within the past five years. For example, consider the violent protests in Ferguson, MO following the shooting of a Michael Brown, a black teen, by a white police officer (Dolan, Shallwani, & Kesling, 2014), the armed revolt by patriot groups and rancher Cliven Bundy in the South-Western United States (Fuller, 2014), the murder of two police officers by a couple who left a swastika and a Gadsden ("Don't Tread on Me") flag at the scene and that participated in the Bundy revolt (Shoichet, Lah, & Fantz, 2014), the attempted assassination of Gabriel Giffords in Tucson, AZ (Thornburgh, 2011), the Boston Marathon Bombing (Chasmar, 2013), and the murder of nine congregants, including a state senator, by a racial terrorist at an African American church in Charleston, SC (Robles, Horowitz, & Dewan, 2015).

I am writing this dissertation in the midst of the 2016 Presidential Primary. Donald Trump has currently clinched the Republican Party's nomination for President of the United States. Trump's campaign is characterized by populist messages advancing policies such as building a wall to secure the border between the United States and Mexico and banning all Muslims from the U.S., while continually utilizing his campaign to launch character attacks at "war heroes, racial groups, women, news anchors and entire

religions" (Grim, 2016, para. 8). Due to the radical rhetoric and policy positions advanced by Trump, the Huffington Post has begun to conclude each article about Trump with the following phrase: "Note to our readers: Donald Trump is a serial liar, rampant xenophobe, racist, misogynist, birther and bully who has repeatedly pledged to ban all Muslims – 1.6 billion members of an entire religion – from entering the US" (as quoted in Greenslade, 2016, para. 2).

On his way to leading the race, Trump has ridden a tidal wave of anger and outrage most prominently indicated by repeated incidents of political violence. Protestors and journalists at Trump events have been spit on, punched, shoved, kicked, and forcibly removed by Trump supporters and security (Lind, 2016; Mathis-Lilley, 2016). Trump has spouted encouragement and promised legal protection to his supporters committing these acts, stating: "If you see somebody getting ready to throw a tomato, knock the crap out of 'em, would you? Seriously. Okay? Just knock the hell — I promise you, I will pay for the legal fees" (as quoted in Lind, 2016, para. 9). In a Republican Presidential Primary Debate on March 10, 2016 hosted by CNN and moderated by Jake Tapper, Trump responded to question on the violence at his rallies with the following: "There is some anger. There's also great love for the country. It's a beautiful thing in many respects. But I certainly do not condone that at all, Jake" (as quoted in Lind, 2016, para. 29). While Trump's supporters that turned violent may have been acting out of anger, or even love for country, there are perhaps other explanations for this phenomenon. In this project, I explore the attitudinal and communicative covariates of political violence, continuing and extending my line of research into this topic (e.g. Hawthorne, 2013; Hawthorne & McKinney, 2013; Hawthorne & Warner, 2013).

I define political violence as a specific form of political behavior and argue that the decision to engage in political violence follows the same type of processes associated with other political decision making. Specifically, the decision whether to engage in political violence or another type of political activity (i.e. non-violent political engagement) is made using information processing shortcuts that are associated with attitudes including: in-group bias and the lack of political trust (distrust). Further, I hypothesize that certain types of social and traditional media use impact in-group bias and political trust and are indirectly associated with political violence. I collect cross-sectional data to evaluate the relationships within my theoretical model using a survey deployed during the month of March while the 2016 Presidential Primary Elections were being held and utilizing social media data collection utilizing custom software.

This project contributes to and develops the existing bodies of research surrounding political violence, political behavior, and political communication in several ways. First, I theorize and test the links between two distinct attitudes (in-group bias and political trust), political behaviors (violent and non-violent political engagement), and communication behaviors (social and traditional media use). To measure political violence, I design and validate a self-report measure of attitudes related to communicative and physical political violence. Further, I utilize a novel data collection plan to link the results of quantitative analyses summarizing participant social media communication and self-report survey results to model the relationship between observed communication behaviors and attitudes.

In the following chapters I review my theoretical model outlining the relationships between social media use, traditional media use, in-group bias, political

trust, political violence, and non-violent political engagement. Chapter two begins with a review of the literature surrounding violence and political behavior. I then elaborate on the role of in-group bias, and political trust in the decision to engage in political behaviors including political violence and the dynamic role communication behaviors have with in-group bias and political trust. Chapter three describes the processes utilized to test my theoretic model including describing the cross-sectional survey data that will be utilized, the social media data collection plan and quantitative text analysis methods, a description of the participants, and analyses that will be conducted on the data. I also review the issues associated with measuring political violence and the steps utilized to design and validate a self-report measure of political violence. In chapter four I present the results of my analyses showing that higher levels of in-group are associated with higher levels of non-violent political engagement while lower levels of political trust are associated higher levels of political violence. Further, the results show that pro-attitudinal media use is related to higher levels of in-group bias and lower levels of political trust while being indirectly related to non-violent political engagement and communicative political violence through these attitudinal variables. In chapter five I situate these results in the broader literature covering political behaviors and political communication.

Chapter 2: Literature Review

Violence can take several different conceptual definitions. For example, violence can potentially refer to a broad class of actions, including verbal assaults such as name-calling or incivility and more physical acts of violence such as punching or kicking, or alternatively violence can be defined in a narrow manner, excluding communicative actions from the definition of violence and focusing only on physical assaults (Potter, 1999). I conceptualize of and define violence as any action that violates another's emotional or physical well-being (i.e. Potter, 1999). My broad definition of violence encapsulates both the communicative and physical components of the violence construct. Communicative violence is an action that is communicated (e.g. verbally, non-verbally, mediated) that violates an another's emotional or physical well being, while physical violence is an action that creates physical contact between the actor, or a controlled object, and a target that violates the target's emotional or physical well-being. Physical violence implies contact with the body, which is more likely to directly cause bodily harm to a specific target. Because of the increased likelihood of harm, physical violence is an escalation of communicative violence and is therefore more intense. There are important theoretical reasons to define and measure different intensities of violent behaviors, that I elaborate on later in this chapter.

Previous research has tried to explain how violence is both instrumental, or goal-directed, and an impulsive behavior (C. A. Anderson & Bushman, 2002; Tedeschi & Felson, 1994). From this perspective violence is both a calculated decision directed towards achieving some larger goal and also an impulse driven by specific set of conditions. Also, previous research has also explored a number of different psychological

mechanisms that underpin violent behavior (C. A. Anderson & Bushman, 2002; Bandura, 1973; Berkowitz, 1989; Dollard, Miller, Doob, Mowrer, & Sears, 1939; Huesmann, 1988; Tedeschi & Felson, 1994; Zillmann, 1983). However, little of this research has focused on violence specifically within the political context. Political violence is motivated by politics and functions as a strategic discourse between actors engaged within the political conflict. People may choose to commit political violence for a variety of different reasons, but the action itself is a strategic choice, which implies that political violence is instrumental.

Political violence is a form of political engagement, so at times I refer to political violence as violent political engagement. I mostly use the term violent political engagement to contrast with the term non-violent political engagement. Non-violent political behaviors and non-violent forms of political engagement advance a political goal through the use of other means than violating a someone's emotional or physical well-being. Non-violent political engagement can take on different levels of intensity that include non-confrontational behaviors, such as anonymous voting or donating to parties or candidates, and more intense confrontational behaviors, such as persuading others and actively campaigning for parties or candidates (Mutz, 2002).

Politics is the series of discourses and institutions that manage the conflict between social groups in a society (Mouffe, 2013). All political behavior is a manifestation of the conflict between social groups (Mouffe, 2013). Social groups are a collection of individuals that perceive themselves as a part of the same social category, share an emotional involvement with their common identity, and achieve some degree of consensus regarding the in-group's evaluation and membership (Tajfel & Turner, 1979).

Social group identity is defined by the perceived difference between the individual and the in-group compared to others, implying that the differences between groups are the basis for the creation of an identity and that political conflict is an expression of political identities (Mouffe, 2013). Political parties are one type of institution that organizes social groups within a political conflict (Lipset & Rokkan, 1967). Political behaviors are tied to and motivated by the conflict between social groups in a society, this project is primarily concerned with understanding the different attitudinal and communicative covariates of both violent and non-violent political engagement.

There are likely several different contributing factors and mechanisms that combine to produce violent political behavior. Some researchers have raised concerns that mass political polarization in the electorate may be related to political violence (Iyengar et al., 2012; Sunstein, 2009). By definition political polarization refers to the movement of opinions towards polar opposites among different political groups, though there are several different opinion domains that can be measured at the individual level as indicators of mass polarization (Prior, 2007). While there is much agreement in academic communities that elite political actors are polarized (McCarty, Poole, & Rosenthal, 2006), there is a vigorous debate regarding the existence of mass polarization in contemporary America.

Much of the debate over the existence of mass polarization hinges on the specific opinion domain utilized to operationalize polarization (Hetherington & Weiler, 2009). For example, some evidence shows that regarding several social issue stances, including abortion, most Americans hold nuanced views that compromise positions based on the details of a specific situation, rather than holding views that are polar opposites (Fiorina,

Abrams, & Pope, 2011). Still other evidence shows that recently, public opinions on many policy issues have become more consistent within the parties and diverge between the parties, especially among the most politically active citizens (Abramowitz, 2010). Working from the assumption that the mass public thinks about politics in terms of social groups rather than specific issues, Iyengar and colleagues (2012) found that in-group bias was increasing in the United States, implying that attitudes about opposing political groups are growing more acrimonious while political in-groups are liked much more, indicating that affect political polarization may be occurring.

Rather than becoming more polarized in attitudes it is much more likely that political parties are becoming better sorted along specific sets of policy beliefs and perhaps demographic or personality characteristics (Hetherington & Weiler, 2009). The partisan-ideological consistency has increased among both of the major political parties in the United States, meaning that more people have matched their specific ideological and policy preferences with the party that advances those issues than historically was the case (Abramowitz, 2010). The growing in-group bias in the United States could be a reflection of the increasing partisan-ideological consistency. Given that now more people agree with others in their party regarding policy positions, discussions over policy are more likely to result in agreements, a positive outcome, that may increase affect towards the in-group. Partisan-ideological consistency within parties may also increase the likelihood for disagreements over policy with party outsiders, which may decrease affect for the out-group. Regardless of the aggregate processes of sorting or polarization by which this attitude this affect based in-group bias has developed, in-group bias may be related to the decision to commit political violence.

From a purely rational perspective, the decision to commit violence is based on estimations of gains and costs and consideration of alternative actions within a given context (Tedeschi & Felson, 1994). However, people generally make decisions on how to behave in a specific context with incomplete information about gains and consequences and only a partial contemplation of alternative behaviors (Simon, 1979, 1985). In such incomplete information environments people utilize their feelings to speed up the decision making process by bypassing the estimation of gains, costs, and risks associated with a specific behavior and the consideration of alternative behaviors. Feelings work as information processing shortcuts to speed up the decision making process by making the individual feel as if they know that a particular behavior is best. Politics is one domain where feelings impact decision making in a variety of different ways (Hetherington, 1998, 2005; Lodge & Taber, 2013; Popkin, 1994; Sniderman, Brody, & Tetlock, 1991). The decision to commit political violence is made within a political context and the mechanisms that impact general political decision-making may also impact the decision to commit political violence. In-group bias and political distrust are two key attitudes that work as information processing shortcuts that influence the decision to engage in political behaviors.

A salient social group identity is indicated by strong in-group biases, or affect-based preferences that favor the in-group and disfavor the out-group (Billig & Tajfel, 1973). Most citizens do not evaluate political parties based on policy preferences, but rather think about politics in terms of social group relationships (Iyengar et al., 2012). Therefore in-group bias along political partisan lines is an indicator of the salience of a political identity. In-group bias has been increasing in the United States among

Democrats and Republicans since the mid-1970s, implying that affect polarization, or a population level increase in in-group bias among opposing partisans, characterizes the U.S. population (Iyengar et al., 2012). Feelings of affect act as an information processing shortcut to bias political information processing and decision making (Lodge & Taber, 2013). Further, in-group bias is related to political violence, being observed as a pre-condition for acts of terrorism (Sageman, 2011) and genocide (Burke, 1941; Gupta, 2001). Therefore, in-group bias may be one attitudinal covariate with political violence. However, a derogatory evaluation of out-group members does not necessarily result in hostility (Tajfel & Turner, 1979).

Research has shown that political trust is an important information processing shortcut that helps people to make quick decisions about politics (Hetherington, 1998, 2005). In the broadest definition political trust is an evaluation of a political object, that can be focused towards various groups and people (e.g., specific politicians, government as a whole, regime based institutions, political groups), and is based on whether the groups and people will consistently act with expectations and in the perceived best interests of the individual and community. In perhaps the most narrow definition political trust is, "the degree to which people perceive that government is producing outcomes consistent with expectations" (Hetherington, 2005, p. 9). However, the subject of the feelings of political trust can vary, with some definitions focusing specifically on a group or person, such as one political party, and that actor's performance and others towards general perceptions of diffuse political objects like countries, governments, and regimes (Hetherington, 1998). Frequently definitions of political trust have been adapted from research on interpersonal trust, in which trust is a function of perceived actor motives and

interests and is dependent on an evaluation of whether the actor will behave in the best interest of the individual (Hardin, 1999). While interpersonal trust is solely related to evaluations of behaviors in the best interest of the individual, definitions of political trust expand whose interests are considered and is characterized by an evaluation of whether an actor will behave in the best interest of the general public (Citrin & Muste, 1999).

Political distrust is the opposite of political trust and therefore distrust implies perceptions that a specific political object is a threat to the interests of the individual and community. Long term feelings of diffuse political distrust, or feelings like the political system as a whole actively threatens individual and community interests, "are very likely to be accompanied by hostility toward political and social leaders, the institutions of government, and the regime as a whole" (Miller, 1974, p. 951). However, when distrust is associated with specific political actors and groups then violence is also one potential response to defend the threatened interests of the individual or community (Burke, 1984; Mouffe, 2013). Since both diffuse and specific political trust may be associated with political violence, I measure both varieties of political trust in order to cover the whole content domain associated with political trust. The operationalization of diffuse political trust will focus on trust towards the government as a whole while specific political trust will focus on trust towards the political out-group.

In-group bias and political trust are two attitudes that interact together to make the decision to engage in acts of political violence more likely and as such, in-group bias and political trust are related though distinct constructs. In-group bias is rooted in generalized affect based feelings towards political groups that signal a salient social identity (Billig & Tajfel, 1973). Political trust is similarly more, "affective (feeling) than cognitive

(thinking)" (Hetherington, 2005, p. 51). However, political trust is a feeling derived from perceiving a political subject as predictable and non-threatening. Conversely, distrust or the lack of political trust is associated with perceptions of unpredictability and threat. In-group bias is based on feelings of identification while political trust is based on perceptions of threats and potential gains.

Different political communication behaviors, like pro-attitudinal media use and social media use, may be associated with in-group bias and political distrust. Much of the research on the relationships between in-group bias, political trust, and pro-attitudinal media use has shown that the relationships may be reciprocal though contingent, such that media use is made more likely by the attitude and that media use reinforces the attitude, though the effect is contingent on individual level factors. Similar reciprocal and contingency models guide my inquiry into the relationship between political social media use, in-group bias, and political trust.

A significant portion of citizens' political communication in modern democracies comes from mediated sources (Bennett & Entman, 2001). Traditionally in the United States, media has operated on a few-to-many, or broadcast model, of political information exchange which resulted in a more-or-less uniform level of political information across the body of the media viewing population (Prior, 2007). The proliferation of cable television increased the variety of content available on television media and many selected out of the political media environment in favor of consuming more entertaining options (Prior, 2007). However, this increased media choice has also enabled partisan audiences to select into pro-attitudinal, attitude confirming, friendly partisan media environments (Garrett, 2009; Goldman & Mutz, 2011; Iyengar & Hahn, 2009). Pro-

attitudinal media, which is a media source that is selected by an individual that confirms previously held political views, has been linked to in-group bias by research focusing on discovering the causal dynamics of selective exposure (Arceneaux & Johnson, 2013; Feldman, Myers, Hmielowski, & Leiserowitz, 2014; Garrett, 2009; Garrett et al., 2014; Garrett & Stroud, 2014; Levendusky, 2013; Slater, 2007; Stroud, 2007). Research has also explored the complex relationship between traditional political media consumption (e.g. television news), partisan media consumption (e.g. cable news and campaign communication), and political trust (Avery, 2009; Cappella & Jamieson, 1997; Norris, 2000; Valentino, Beckmann, & Buhr, 2001).

The spread of the Internet across the United States has destabilized the traditional political communication environment while extending and pluralizing the public sphere (Dahlgren, 2005). Social media platforms have allowed the public to easily post information creating the potential for a many-to-many model of political information exchange. There are a variety of different types of social media ranging from social network sites (boyd & Ellison, 2007), such as Facebook, micro-blogs (J.-H. Schmidt, 2013), like Twitter, news-aggregator websites, like Reddit, and a range of commenting systems on news websites and other sources of political media. Each of these social media platforms enables the spread of voices in the public sphere and provide citizens expanded opportunities to express themselves politically.

In this project, I explore the links between the consuming and posting political media and political attitudes including in-group bias and political trust. I theorize and test the relationship between in-group bias, political trust, and both non-violent and violent political behavior. I also explore the indirect link between communication behaviors

including consuming pro-attitudinal political media and posting political content on social media and political engagement. However, first I review the literature surrounding violence and position political violence as a type of political behavior.

Political Behavior and Violence

Violent behavior is a decision that cannot be separated from the surrounding context. Political violence is a political act and therefore the same attitudes and processes that influence the decision to engage in political behaviors are also likely associated with the decision to pursue political violence. These thoughts on general violence, political violence, and political behavior are informed by the significant bodies of previous research addressing these topics.

Theories of Violence

Nearly every field within the social sciences has theorized about the processes and mechanisms that cause violent behavior resulting in an diverse set of perspectives on violence (Tedeschi & Felson, 1994). For example, violence has been theorized as a drive-based reaction to aversive stimuli (Berkowitz, 1989, 1993; Dollard et al., 1939), an arousal-based reaction (Zillmann, 1979, 1983), a learned behavior (Bandura, 1973, 1983; Huesmann, 1988), and most recently as a decision influenced by several contextual and individual level factors (C. A. Anderson & Bushman, 2002; Tedeschi & Felson, 1994). In this project, I conceptualize violence as the outcome of a decision that occurs within a specific context and political violence occurs specifically within the political context. Political violence is instrumental, or goal directed, and therefore theories that focus on instrumental violence are the most applicable to my theory of political violence.

Reaction Theories of Violence. The drive-based reaction theories of violence define violence as an uncontrollable reaction to an aversive experience. Perhaps the earliest scholarly inquiry into violent behavior posited that frustration, or any event or act by others that prohibits the attainment of a pursued goal, creates aggressive energy which must be released in violent outbursts unless the individual is acted on by some inhibitory force (Dollard et al., 1939). In this view, violence is the outcome of a drive-based process that generates an impulsive response when aggression reaches some level and violence therefore operates separately and differently from other psychological mechanisms (Berkowitz, 1989). Based on evidence suggesting that not all frustrations were aversive stimuli, Berkowitz (1989) revised this thesis to suggest that frustrations could lead to aggression if the frustration caused feelings of negative affect. From the perspective of drive-based theories, all violence, including goal directed violence, is inherently based on an impulsive reaction driven by aggression (Berkowitz, 1993).

The arousal-based reaction theories posit that physiological arousal triggers the decision to commit a violent act. Physiological arousal is a diffuse and undifferentiated feeling that is interpreted in different ways depending on the surrounding context (Schachter, 1964). Unlike aggressive energy, physiological arousal can be dissipated by means other than violence (Zillmann, 1979). Heightened arousal can be interpreted as anger or fear which amplifies any aggressive behavior that is chosen by the individual (Zillmann, 1983). Zillmann (1979) further, posits that arousal from two sources can be combined together and interpreted as coming from a single source, through a process called arousal transfer.

The drive-based theories of violence focus on impulsive violence and extend their claims to cover instrumental violence. However, the motives associated with impulsive and instrumental violence are conceptually distinct and therefore impulsive and instrumental violence may be caused by different mechanisms. Further, my focus in this project is on instrumental violence and therefore the drive-based theories are less applicable than others. Both the reaction theories explain violence utilizing an energy that builds and must be dissipated by some means, while my theory positions violence as a decision. Also, both the drive and arousal based reaction theories try to describe violence generally and I view the decision to commit violence as a contextual action that may operate differently dependent on the surrounding context. Both reaction based theories of violent behavior have undergone extensive focus by research teams and the evidence supporting these theories is at times contradictory and lacking in validity (Tedeschi & Felson, 1994).

Learning Theories of Violence. Research focusing on how violent behaviors are learned moved away from the impulsive reaction framework and began to conceive of violence as a decision. Huesmann (1988) argues that cues in the environment cause the retrieval and activation of aggressive scripts. Scripts are retrieved from memory when a person is exposed to cuing social situations and are activated when the script is evaluated as an appropriate response, using a process that is potentially impacted by heightened emotions (Huesmann, 1988). According to this perspective violence is a learned, scripted response to specific stimuli that is selected for performance under a set of specific conditions.

Bandura (1973) views violence as a learned response to negative stimuli. Negative events facilitate violence when people have previously learned to respond with violence to negative stimuli. People weigh the perceived gains against perceived costs of a behavior and if the net gains of violent behavior outweigh the gains of alternative actions then violence is likely (Bandura, 1973). People learn to estimate the gains and costs of a specific behavior by observing models of behaviors and noting the experienced consequences (Bandura, 1983). From this perspective, people learn to commit violence by observing people experience positive consequences for violent behavior.

Each of these theories provides slightly different explanations for how violence is learned and describe slightly different causal mechanisms associated with violent behaviors. Both of these theories conceive of violence as a decision, but the decision is based on different considerations; Huesman focuses on perceived appropriateness while Bandura focuses on an estimation of gains and costs. Further, both of the learning theories assume that there are general considerations that impact the decision to commit violent behavior in every context. In my view there are a number of different considerations and processes that underpin the decision to commit violence and the factors are dependent on the context within which the behavioral decision is made.

Decision Theories. There are two major theories that explicitly position violence as a decision. These two theories were developed because the inability of the earlier reaction-based theories to explain the entirety of violent phenomena and in response to the development of the learning theories that position violence as a decision (C. A. Anderson & Bushman, 2002; Tedeschi & Felson, 1994). Anderson and Bushman (2002) position violence as the outcome of an impulsive or thoughtful decision that is impacted

by existing emotions (i.e. fear or anger), physiological arousal, and individual factors such as aggressiveness and existing cognitions. Tedeschi and Felson (1994) position violence as the outcome of a decision made within the context of a specific social situation and as rooted within motivations to coerce behavior.

My theory of political violence has much in common with the decision based theories of violent behavior. Anderson's and Bushman's model again suffers from the conceptual issue of attempting to explain both reaction-based and instrumental violent behaviors. These two types of violence may operate under different causal processes. My conception of violence aligns most closely with that of Tedeschi and Felson, since we view violence as intimately tied to the social situation. However, while Tedeschi and Felson associate the motivations for violence with coercion, I view the motivations and processes tied to the decision to commit violence as directly related to the specific social situation that the decision occurs within. Violent behaviors occur for the same reasons that people engage in other types of behaviors and the motivations for behaviors vary by context. I conceive of political violence as one type of political behavior, and therefore, the decision to commit political violence is likely impacted by the same types of attitudes and processes that impact political decision making more generally.

Assumptions about Political Decision Making

The assumptions made about political actors and the considerations that impact political decision making impact the causes of political behavior that are explored within academic research. For example, one common assumption utilized to explain political behavior posits that people are rational actors who evaluate the potential gains and consequences of all behavior options and then chose the specific behavior that maximizes

gains and minimizes losses. This theory of objectively rationale actors was borrowed from neoclassical economics and statistical decision theory (Simon, 1985). From the perspective of the rational actor model, the causes of political behavior are restricted to estimations of gains and costs along with the considerations of alternative behaviors.

While perhaps a useful simplifying assumption, the rational actor model is not particularly helpful in explaining actual political behavior (Simon, 1985). For example, in all but the closest elections a purely rational actor would not vote because it is likely that an estimation of the time and resource costs required to vote would outweigh the value attained from voting. Similarly, in most cases the rational actor model fails to predict political violence since a rational actor would likely estimate the risk of failure and the costs of individual punishment associated with engaging in political violence as higher than the chance for success and the potential gains that success would entail.

Taking a page from cognitive psychology, I assume that people are goal oriented and search for the best decision to achieve that goal but that, "the search is incomplete, often inadequate, based on uncertain information and partial ignorance, and usually terminated with the discovery of satisfactory, not optimal, courses of action" (Simon, 1985, p. 295). Political actors make decisions within a bounded rationality, where decisions are made quickly with incomplete information about alternatives and using information processing shortcuts (Simon, 1979). A significant body of research shows that people use various attitudes and different types of information processing shortcuts to help them make political decisions (Hetherington, 1998; Lodge & Taber, 2013; Popkin, 1994; Sniderman et al., 1991). Information processing shortcuts work by bypassing the estimations of gains, costs, and alternatives when considering a behavior in

order to speed up the process of making a decision. For example, high in-group bias may be used as a shortcut to bypass the estimation of the gains and costs of voting and may lead people to feel that they know the value gained from engaging in voting behavior is high.

The decision to commit political violence is likely impacted by attitude based information processing shortcuts, though there has been little research into the attitudinal preconditions associated specifically with political violence. What research does exist utilizes evidence derived from limited samples (Sageman, 2011), qualitatively examined exemplars (Gupta, 2001), political theory (Mouffe, 2013), and rhetorical criticism (Burke, 1941, 1984). In-group bias and political trust are two attitudes that are linked to political violence in these accounts.

In-group Bias, Political Distrust, and Political Behavior

In-group bias and political trust are two distinct attitudes that work as information processing shortcuts, allowing people to bypass the considerations made when deciding whether to engage in politics and whether that political engagement will take violent or non-violent forms. In-group bias and political trust interact to influence political behavior, including the decision to commit political violence. See Table 1 for an illustration of this dual-attitude interaction.

Table 1

Dual Attitude Model of Political Behavior

	Low In-Group Bias	Med. In-Group Bias	High In-Group Bias
High Trust	Low Engagement	Voting, Donating	Volunteering, Persuading
Low Trust	Low Engagement	Comm. Violence	Physical Violence

The first component of the interaction in my dual attitude model is in-group bias, or the extent someone identifies with a particular social group within the political conflict, which influences the intensity of political engagement. The more someone identifies with a particular party the more likely they will be to engage in comparatively higher risk political behaviors like confrontational non-violent engagement including volunteering and persuading others and physical political violence. As identification with a political group declines so does the intensity of engagement and people are more likely to only engage in less risky political behaviors like non-confrontational political engagement including voting and donating and communicative political violence. In-group bias is a feeling that makes people believe they are the type of person who acts on behalf of a particular social group.

Accounts of several extreme forms of political violence argue that in-group bias has a role to play. The public trials and investigative documents of convicted Islamic terrorists show that their actions are in part motivated by views of the West as an all-powerful, evil, and existential threat combined with total devotion to and reliance on other terrorist cell members (Sageman, 2011). Burke's (1941) rhetorical analysis of *Mien Kampf* argues that Hitler invited Nazi Germany to commit genocidal violence by

inspiring hatred for Jews and demanding intense nationalistic love. Collective madness, such as the Rawandan and Serbian genocides, is enabled in part by intense feelings of hatred towards the "them," the targets, and intense feelings of love for the "us," the perpetrators (Gupta, 2001). In-group bias could act as an information processing shortcut in the moment people are deciding whether to engage in political violence, causing people to bypass the estimations of gains and costs associated with violent political engagement and increasing the likelihood of a person deciding to commit political violence.

In-group bias is also likely related to non-violent forms of political engagement. Previous research has found that political ambivalence, in part a function of low in-group bias, is associated with not engaging in non-violent political behavior, such as voting and volunteering (Mutz, 2002, 2006). It is likely the case that the converse of this finding is true, such that as in-group bias increases a person becomes more likely to engage in non-violent political behavior. Engagement with the political process takes time and energy. Identification with a political party, as indicated by in-group bias, provides a person a stake in the political conflict. At higher levels of in-group bias people feel more attached to the political in-group and this attachment likely inspires them to action.

Both the specific and diffuse varieties of political trust likely impact whether a political act takes violent or non-violent forms. High diffuse political trust implies that someone trusts the political system to consistently serve their and the community's best interest. High specific political trust implies that a specific subject is viewed as unthreatening and who acts consistently in the perceived interests of the individual and/or community. A person with high trust would likely estimate that non-violent political

engagement is a good way to achieve political goals. As a result, the person will be more likely to engage in forms of non-violent political engagement because they feel that the political system and the political opponents are generally serving the best interests of the individual and community.

Diffuse and specific feelings of political trust are low when the subject of the trust evaluation is viewed as a threat to perceived individual and public interests. Long term feelings of low diffuse political trust are likely to result in political violence (Miller, 1974). We turn towards violence as a tool to solve political problems when we perceive the opposing actors as "threatening *our* existence" (Mouffe, 2013, p. 5, emphasis in original), threatening individual or community interests, or acting unpredictably. Similarly, Burke (1984) argues that constructing actors with the tragic frame, that is framing an actor as a threatening villain, invites the audience to view violence against the actor as an appropriate action. Low political trust could lead someone to estimate that not engaging in violent behavior to mitigate a perceived threat poses a higher risk than engaging in political violence, failing in the effort, and bearing the costs associated with punishment. Therefore, low political trust is likely associated with political violence.

The decision to commit political violence is primarily motivated by political trust, but the intensity of the violent behavior is impacted by in-group bias. For example, if a person is distrustful and experiences high in-group biases, then physical violence within the political conflict may be viewed as an appropriate response, while lower in-group biases may lead a person to communicative violence, a less severe violent behavior. In-group bias also impacts behavior in high trust situations and leads people to engage non-confrontational forms of non-violent political engagement such as voting or donating

money. Further, in high trust situations, high levels of in-group bias are associated with confrontational non-violent political engagement such as attempting to persuade others or volunteering for campaigns. In-group bias and political trust interact to produce either violent or non-violent engagement and different intensities of engagement.

Hypothesis 1: High political trust and high in-group bias interact to predict non-violent political engagement including (a) non-confrontational engagement and (b) confrontational engagement.

Hypothesis 2: Low political trust and high in-group bias interact to predict violent political engagement including (a) communicative violence and (b) physical violence.

The Role of Communication Behaviors

However, both in-group bias and political trust are influenced by a number of different exogenous factors. For example, diffuse political trust is likely to be lower than average in the partisan group that is currently out of power since their partisanship will lead them to trust the ruling regime less (Theiss-Morse, Barton, & Wagner, 2015). Different communication behaviors including pro-attitudinal media use and political social media communication may also be related to both in-group bias and political trust.

Communication behaviors within a political context such as consuming political news or discussing politics using social media are types of political behaviors. Therefore, the decision to engage in political communication may also be influenced by the same information processing shortcuts that impact other political decisions. Further, engaging in communication behaviors may reinforce the attitudes that impact political decision. Below I elaborate on the relationships between communication, specifically pro-

attitudinal media use and social media communication, and attitudes, specifically in-group bias and political trust.

Pro-Attitudinal Media Use

Stroud (2008, 2010, 2011) provided significant evidence suggesting that the development of partisan media was enabling some amount of partisan selective exposure and that partisan selective exposure may be was related to polarization. Further research elaborated on these findings, showing that partisans generally do not avoid counter-attitudinal views and news media (Garrett, 2009), but that partisans do tend to selectively expose themselves to pro-attitudinal news media (Garrett & Stroud, 2014; Iyengar & Hahn, 2009). Most people experience friendly media environments that support existing political views and this trend is exacerbated in countries where the each political party has a corresponding media outlet and people can select media based on their partisan beliefs (Goldman & Mutz, 2011). When deciding what political media to consume, partisans may use in-group bias to bypass estimations of the costs and gains of consuming each specific media type and the search for alternative choices, resulting in an assumption that pro-attitudinal sources are the best source to consume. This assumption could be under-girded by any of many different reasons, such as the perceptions that pro-attitudinal sources are higher quality or accuracy. However, whatever reasons provided to support partisan media selection are likely rationalizations that are applied to a gut affective feeling associated with an attraction to pro-attitudinal voices (see Lodge & Taber, 2013), and the affective feelings are a result of perceptions of a shared political identity.

As a consequence, pro-attitudinal media consumption further increases positive affect toward in-group members and negative affect toward out-group members (Garrett et al., 2014; Levendusky, 2013). Exposure to pro-attitudinal media may increase the accessibility of attitudes related to partisan identity (Knobloch-Westerwick & Meng, 2011), therefore increasing the ease with which attitudes associated with in-group bias are accessed and promoting greater identification with political social groups. However, the effect of pro-attitudinal media consumption on in-group bias is moderated by how much political media the individual normally consumes, such that the effect on those who normally consume a lot of political media is negligible (Arceneaux & Johnson, 2013). In the aggregate the polarizing effect of partisan media is rather small, since most people don't consume partisan media and those who do consume partisan media are more resistant to the effects of partisan media on in-group bias (Arceneaux & Johnson, 2013).

Nevertheless, while partisan media may not be contributing to mass polarization, long term continual exposure to partisan media may lead to individual level partisan extremism. In-group bias and pro-attitudinal media consumption are in a positive and reciprocal relationship, such that exposure reinforces in-group bias and in-group bias is related to further selections of pro-attitudinal media (Feldman et al., 2014; Slater, 2007), implying that over a long time and through many repeated exposures, pro-attitudinal media may increase in-group bias among consumers. Previous research has revealed a strong association between in-group bias and pro-attitudinal media consumption going both causal directions and therefore, within my cross-sectional data I expect to find a relationship between pro-attitudinal media use and in-group bias.

Hypothesis 3: In-group bias is positively associated with pro-attitudinal media consumption.

There may also be an indirect relationship between pro-attitudinal media use and other political behaviors including both violent and non-violent political engagement. As previously reviewed, in-group bias may be related to the intensity of engagement in both violent (Burke, 1941; Gupta, 2001; Sageman, 2011) and non-violent political behavior (Mutz, 2002, 2006). Pro-attitudinal media use is linked to increasing in-group bias (Garrett & Stroud, 2014; Levendusky, 2013), though the effect is greatest among weak partisan identifiers that normally do not consume partisan media or engage much in politics (Arceneaux & Johnson, 2013). There is some evidence suggesting that exposure to negativity in political advertising may be related to greater acceptance of political violence, though this effect was contingent on partisanship and the target of the negative advertisement (Hawthorne, 2013; Hawthorne & Warner, 2013). Further, exposure to a debate message, which may be perceived as threatening, increases in-group bias, which is also linked to the acceptance of political violence (Hawthorne & McKinney, 2013). This implies that communication, specifically negative political communication that may be similar to pro-attitudinal media use in may ways, may be indirectly related to political violence, through in-group bias. In this project I test if pro-attitudinal media use is indirectly related to the intensity of non-violent and violent political behavior through in-group bias, a link that has not been tested by previous research directly.

Research Question 1: Is there an indirect effect between pro-attitudinal media use and the intensity of (a) non-violent or (b) violent political engagement through in-group bias?

Similar reciprocal effects have been observed between political trust and media use, though the exact nature of the relationship between political trust and pro-attitudinal media use is cloudy. Those who are most engaged, interested, and trusting may pay the most attention to political news and therefore learn more about government and policies (Norris, 2000). This increase in political knowledge of the occurrences in government may cause an increase in political trust, which subsequently results in even greater news media exposure (Norris, 2000). From this perspective, media exposure and political trust from a mutually reinforcing virtuous circle (Norris, 2000), a process that suggests surveillance may breed trust.

However, further research suggests the that exposure to media may have a more complex relationship with political trust. For example, further research exploring the impact of political trust on media consumption found only modest, non-significant, differences between the media use of the politically trustful and distrustful (Avery, 2009). Further, some evidence shows that exposure to strategic and conflict-oriented frames in media actually increase cynicism and lower levels of political trust (Cappella & Jamieson, 1996), and exposure to political disagreements on television may be perceived as violate established social norms associated with civility and makes people more distrustful of politics (Mutz & Reeves, 2005).

Research on the impact of pro-attitudinal media consumption on political trust may also be contingent on several different variables. For example, the impact of media use on political trust may be moderated by existing levels of trust, such that the distrustful are mostly unaffected by the media while the trustful experience gains in trust through consumption of newspapers and losses in trust through consumption of television news

(Avery, 2009). Further, the impact of strategy frames on cynicism and trust in government is moderated by political sophistication, such that non-partisans and those with less than a college degree are significantly demobilized by exposure to strategy frames but that those who are politically involved and highly educated are mostly unaffected (Valentino et al., 2001).

Media use may have a very complex relationship with political trust that is dependent on the whether the individual is political sophisticated, and likely regularly consumes partisan media, as well as the type of media that is consumed. Given the overall prevalence of negative and polarized voices in partisan media (e.g. Levendusky, 2013), it is likely that pro-attitudinal media will contain strategy and conflict oriented frames that decrease political trust. Therefore, within my cross-sectional data I expect to observe a negative relationship between political trust and pro-attitudinal media use.

Hypothesis 4: Political trust is negatively associated with pro-attitudinal media consumption.

Given that pro-attitudinal media use may be associated with lower levels of political trust, it could be the case that there is also an indirect effect between pro-attitudinal media use and violent and non-violent political engagement through political trust. Previous research has not engaged this possibility and I explore this with my data.

Research Question 2: Is there an indirect effect between pro-attitudinal media use and the intensity of (a) non-violent or (b) violent political engagement through political trust?

In-group bias and political trust may be in a reciprocal, though contingent, relationship with pro-attitudinal media use. Similar contingent and reciprocal

relationships that have been observed between pro-attitudinal media and both in-group bias and political trust use may also be observed in the relationship between political social media use and both in-group bias and political trust. Below, I also explore the possibility that political social media use might be indirectly related to political behavior through the in-group bias and political trust attitudes.

Social Media Use

Previous research has shown that posting on social media about politics is related to a number of different political attitudes. For example, participating in online discussion via social media about salient political events like debates and scandals is systematically related to attitudes towards candidates (Hawthorne & Warner, 2015). The frequency of candidate mentions in tweets posted during a debate is associated with changes in candidate evaluations (McKinney, Houston, & Hawthorne, 2014). Along with impacting candidate evaluations, live-tweeting a debate increases evaluations of debate importance and promotes greater attention to the debate compared to watching the event without a second screen (Houston, Hawthorne, Spialek, Greenwood, & McKinney, 2013). Further, those who engage in live-tweeting behaviors while watching debates tend to recall more statements made by candidates during the debate (Houston, McKinney, Hawthorne, & Spialek, 2013). Some evidence shows that compared to watching alone, engaging in live-annotation of a political debate via social media is associated with greater enjoyment of the debate watching experience and is also associated with consuming more debates (Thorson, Hawthorne, Swasy, & McKinney, 2015). Data collected from the 2012 Taiwanese presidential elections showed that active engagement in political discussion on Facebook was directly associated with offline engagement among young, first time

voters, and passively reading Facebook discussion was indirectly related to offline political participation and voting among all age cohorts through perceptions of Facebook use (J.-H. Lin, 2016).

Political social media communication is likely related to in-group bias. In-group bias is associated with the intensity of political engagement such that people who experience more bias tend to engage more. In-group bias may cause people to bypass the estimation of costs and alternatives associated with posting on social media about politics online and may cause estimations that engaging in social media communication about a political topic is necessary, ultimately resulting in more frequent posts about politics. Further, posting on social media about politics could reinforce in-group bias, which could subsequently lead to further offline and online political engagement. However, any reciprocal relationship between social media use and in-group bias is likely contingent on individual level factors much like the reciprocal models that are used to describe the relationship between pro-attitudinal media consumption and in-group bias. However, within my cross-sectional data I expect to observe a positive relationship between in-group bias and the frequency of political social media use

Hypothesis 5: In-group bias is positively associated with the frequency of political social media use.

Given that the frequency of social media posts about politics is likely related to in-group bias, and in-group bias leads to further, more intense political engagement, there may be an indirect effect between the frequency of posting on social media about politics and both violent and non-violent political engagement through in-group bias. Talking about politics on social media is a form of political engagement and the author is making

an investment of time and energy in order to engage. This sacrifice of time and energy likely increases association with the political group that the author identifies with, thereby increasing in-group bias. In-group bias then may impact the decision whether to engage in both violent and non-violent political behaviors. I explore the potential of this indirect relationship with my cross-sectional data.

Research Question 3: Is there an indirect effect between the frequency of political social media use and the intensity of (a) non-violent and (b) violent engagement through in-group bias?

Political trust is likely associated with the sentiment used in political social media communication. Many of the content features in traditional partisan media, including the strategy frames and displays of incivility that are related to low levels of political trust (Cappella & Jamieson, 1996; Mutz & Reeves, 2005), many times utilize negative sentiment. Political trust is an evaluation of whether political actors will meet expectations of performance with a positive (i.e. trust) and negative (i.e. distrust) dimension. Negative sentiment used in political social media communication reveal the level of distrust associated with politicians and the government in the mind of the author. Conversely, positive sentiment in political social media communication may be related to higher levels of trust. The positive sentiment used in online political discussion may be a reflection of the positive attitudes, including trust, that are associated with politics and politicians. Much like with the other reciprocal, though contingent, models, I expect that the causal impact of sentiment on trust may be strongest amongst those who are not normally politically engaged and are weak partisan identifiers, though within my cross-

sectional data I expect to observe relationships between trust and sentiment use in social media communication.

Hypothesis 6: Low political trust is associated with negative sentiment in political social media communication.

Hypothesis 7: High political trust is associated with positive sentiment in political social media communication.

Political social media communication may also have a connection to the decision whether political engagement takes violent or non-violent forms through political trust. The sentiment of authored communication reinforces the aligning dimension of political trust; negativity results in distrust while positive sentiment is associated with trust. Political trust is then related to whether political engagement takes violent or non-violent forms. The impact of sentiment on trust may ultimately be related to the decision whether to engage in politics violently or non-violently, which would be indicated by an indirect effect observed in my data.

Research Question 4: Is there an indirect effect between the sentiment associated with political social media communication and the intensity of either (a) violent or (b) non-violent political engagement through political trust?

I am also interested in exploring if any emergent content features used in political social media are related to in-group bias and political trust. Several quantitative text analysis methods will be utilized to summarize the body of content produced by participants in this study and extract commonly referenced subjects. I review the quantitative text analysis method in chapter three, but here I posit research questions about this analysis.

Research Question 5: Is in-group bias associated with the use of any subjects used in political social media communication?

Research Question 6: Is political trust associated with the use of any subjects used in political social media communication?

I also propose to examine the indirect relationship between the emergent subjects used in social media communication and political engagement through in-group bias and political trust. Referencing specific subjects may act to reinforce in-group bias and political trust attitudes, which then could subsequently influence the intensity of engagement and whether the engagement is violent or non-violent.

Research Question 7: Is there an indirect effect between the subjects associated with political social media communication and non-violent political engagement through (1) political trust, or (2) in-group bias?

Research Question 8: Is there an indirect effect between the subjects associated with political social media communication and violent political engagement through (1) political trust, or (2) in-group bias?

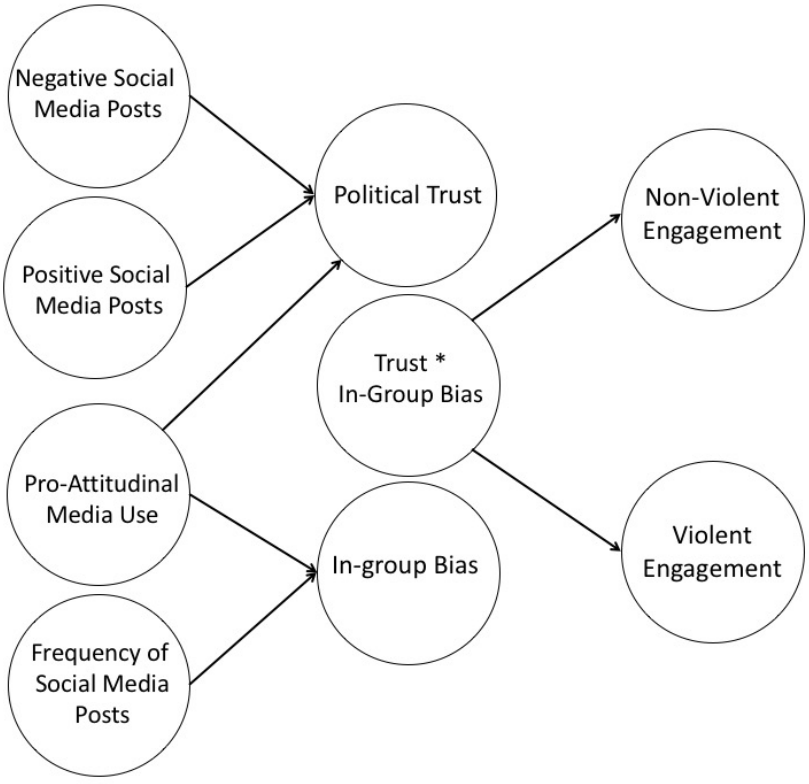
Conclusion

This project is focuses primarily on explaining the attitudinal and communicative covariates of political violence. However, political violence is another form of political behavior and therefore to fully account for the causes of political violence the causes of other non-violent types of political behavior must also be factored into the theoretical model. Political distrust including perceptions of threat, in-group bias, and political communication behaviors such as pro-attitudinal media use and political social media communication all factor into my theoretical model predicting political behavior. Some

evidence suggests that the relationships between political trust, in-group bias, and pro-attitudinal media use are reciprocal though contingent on individual level factors such as political sophistication and experience. I extend this reciprocal and contingent model to explain the relationship between political social media communication, in-group bias, and political trust. The hypothesized relationships summarized by the model are outlined in Figure 1.

Figure 1

Hypothesized Relationships



In the next chapter I outline the methods and approach I will utilize to test my model of political behavior and violence. Also, I describe the process of designing and validating a measure to work as an indicator of political violence. Further, I elaborate

further on the quantitative text analyses utilized to measure the content in social media communication.

Chapter 3: Method

In this project I seek to explore the theoretical links between political social media use, pro-attitudinal media consumption, in-group bias, political trust, and both violent and non-violent political behaviors. I deploy a survey and collect social media content that has been posted by participants to model the relationships between these variables. The results of quantitative text analysis summarizing the political social media communication are linked directly to self-report survey measures that assess relevant constructs. The modeling process presents two methodological difficulties: there is no validated self-report measure of political violence covering a broad content domain of political violence and some types of quantitative text analysis may introduce too much Type I error into estimations in order draw valid conclusions

Validity is the strength of connection between a measurement on an indicator and the construct being measured (Cronbach & Meehl, 1955). Evidence can be gathered showing the validity of different measures and indicators, including both self-report evidence and content analysis results, and therefore validity is a useful criterion of evidence quality. "Validation provides compelling reasons for taking the results of scientific research seriously" (Krippendorff, 2013, p. 329). Along with testing my theoretic model I design a new self-report measure of political violence and gather evidence of validity supporting the self-report and quantitative text analysis.

In this chapter, I outline the process that I utilize to test my theoretic model including the survey and social media data collection. Where applicable, I review the problems with validity associated with measuring political violence utilizing a self-report measure and the steps I take, using psychometric methods, to design and validate the self-

report measure of political violence. I also outline the issues of error control associated with quantitative text analysis and describe the methodological processes to gather evidence for the validity of content analysis measures. Finally, I outline the participants who participated in this project and my data analysis plan.

Survey Data Collection

I collected survey data from March 7, 2016 through March 18, 2016 from a convenience sample of college-aged students. The presidential primary elections in the state where data was collected was held on March 15, 2016, implying that data was collected during a time period where many may have been thinking about, talking about, and participating in political action. All of the survey data was collected online via the Qualtrics online survey platform.

Measures and Scales

Participants completed several different self-report measures (See Appendix 1 for self-report scales and response options). In the survey participants were prompted to log into each social media platform, including Facebook, Twitter, Reddit, and Disqus, in order to provide permission for their historic social content to be collected for this project. Custom programs automatically collected posts made by participants and stored them in a local database when participants provided permission.

Within the survey I measured the **demographics** of my participants. Specifically, participants reported their age, sex, and race/ethnicity at the end of the survey. Participants also identified their partisanship, on a range from 1 (*Strong Democrat*) to 7 (*Strong Republican*), and ideological stance, on a range from 1 (*Extremely Liberal*) 7 (*Extremely Conservative*).

Political trust, and the lack of political trust, is related to violent political engagement. I measure political trust in two similar but different ways. **Specific political trust** is an indicator of trust in a specific political object, and in this project I am interested in assessing political trust associated with political others. Craig, Niemi, and Silver (1990) present a measure of incumbent based trust which was slightly adapted for this project by replacing references to an incumbent with references to specific partisan groups. The responses on this trust scale are on range from 1 (*Completely Disagree*) to 7 (*Completely Agree*) and include the following items, where [Democrats/Republicans] is filled in with the participant's opposing political group: "You can trust [Democrats/Republicans] to do what is right.", "It often seems like [Democrats/Republicans] are run by a few big interests looking out for themselves rather than being run for the benefit of all people." (Reverse coded), "Most elected [Democrats/Republicans] try to serve the public interest, even if it is against their personal interests.", "When [Democrats/Republicans] make statements to the American people on television or in the newspapers, they are usually telling the truth.", "Unless we keep a close watch on them, many [Democrats/Republicans] will look out for special interests rather than for all the people.", "[Democrats/Republicans] in public office usually try to keep the promises they have made during the election.", "Most elected [Democrats/Republicans] are well-qualified to handle the problems that we are facing in this country.", "Quite a few [Democrats/Republicans] are not as honest as the voters have a right to expect." (Reverse coded), "Most [Democrats/Republicans] can be trusted to do what is right without our having to constantly check on them."

However, this measure of specific political trust does not fully capture the content domain of the political trust construct. Specifically, the measure does not completely cover the content domain associated with the lack of political trust because no questions assess perceptions of the out-group as a threat to values, interests, and existence. Therefore, I utilize six more items to assess political trust towards the out-group member towards the low end of the trust scale that measure how threatening the other is perceived to be. The responses on this trust scale are on a 1 (*Completely Disagree*) to 7 (*Completely Agree*) and include the following items, where the term [Democrats/Republicans] shows the individual participant's opposing political group: "Most [Democrats/Republicans] want to hurt the United States.", "[Democrats/Republicans] in office deliberately try to harm Americans.", "Quite a few [Democrats/Republicans] do not truly love the United States,", "[Democrats/Republicans] in office create immoral laws", "If a [Democrats/Republicans] win in the 2016 general election I fear for the financial wellbeing of my family", and "Having a [Democrat/Republican] in office hurts my economic prospects". In this analysis all the specific trust items were scored so that trust is at the high end of the scale and distrust, or perceptions of threat, are at the low end of the scale.

I also measure **diffuse political trust**, or political trust in diffuse political objects like a government or a regime. Diffuse political trust has been historically measured on American National Election Studies (ANES) surveys and other surveys using a metric assessing trust in government, perceived waste, whether the government serves big interests, and whether politicians are corrupt (Hetherington, 1998, 2005). This scale includes the following items and response options: "How much of the time do you think

you can trust the government in Washington to do what is right-just about always, most of the time, or only some of the time?" (responses include 1 (*Just about always*), 0 (*Most of the time*), and -1 (*Some of the time*)); "Do you think that people in government waste a lot of the money we pay in taxes, waste some of it, or don't waste very much of it?" (responses include 1 (*Not very much*), 0 (*Some*), and -1 (*A lot*)); "Would you say the government is pretty much run by a few big interests looking out for themselves or that it is run for the benefit of all the people?" (responses include 1 (*For the benefit of all*) and -1 (*For a few big interests*)); and "Do you think that quite a few of the people running the government are crooked, not very many are, or do you think hardly any of them are crooked?" (responses include 1 (*Hardly any*), 0 (*Not many*), and -1 (*Quite a few*)). In this analysis all the diffuse trust items were scored so that trust is at the high end of the scale and distrust, or perceptions of threat, are at the low end of the scale.

However, this measure of diffuse specific trust also lacked questions at the low end of the trust scale measure perceptions of threat with diffuse political objects. I therefore author five more items to cover this area of the political trust content domain. This factor of the scale includes the following items and response options: Do you think that quite a few of the people running the government want to hurt the United States, not many want to hurt the United States, or do you think hardly any of them want to hurt the United States? (responses include 1 (*Hardly any*), 0 (*Not many*), and -1 (*Quite a few*)); Do you think that the government is not a threat to your economic wellbeing, is some of a threat to your economic wellbeing, or is a big threat to your economic wellbeing? (responses include 1 (*Not a threat*), 0 (*Some of a threat*), and -1 (*A big threat*)); Do you think that the government is run by quite a few people who hate America, is run by not

many people who hate America, or is run by hardly any people who hate America? (responses include 1 (*Hardly any*), 0 (*Not many*), and -1 (*Quite a few*)); Do you think that the government hardly ever harms Americans, sometimes harms Americans, or often harms Americans? (responses include 1 (*Hardly ever*), 0 (*Sometimes*), and -1 (*Often*)); Do you think that hardly any people in the government are immoral, that not many people in the government are immoral, or quite a few people in the government are immoral? (responses include 1 (*Hardly any*), 0 (*Not many*), and -1 (*Quite a few*)).

In-group bias is also theoretically associated with violent and non-violent political engagement and is measured using feeling thermometers on a range from 0 (*Cold Feeling*) to 100 (*Warm Feeling*), that are associated with major political groups (Liberals/Conservatives) and parties (Democrats/Republicans). Normally, a third feeling thermometer is utilized to measure feelings associated with politicians, but given the current fractured nature of the parties in the Presidential primary elections, no single Republican could be used to calculate a clear opposing differential with a Democratic politician (Obama). Therefore, the politician feeling thermometers were excluded from calculating in-group bias. The feeling thermometer scores are utilized to calculate in-group bias by finding the absolute value of the differential between opposing thermometers (Iyengar et al., 2012; Skitka, Bauman, & Sargis, 2005). In the structural and measurement models estimated using structural equation modeling (SEM) the error variance of in-group bias is constrained to one, so that the model can be locally identified.

In this project, I measure the participant's **pro-attitudinal political media consumption**. This can be a difficult task, given that direct self-reports of communication

activities may be unreliable. Survey self-report data of media exposure is often substantially over-reported compared to observational data regarding media exposure (Prior, 2009b). Many participants may not be able to accurately and reliably recall how frequently they engage in media use behaviors (Prior, 2009a). Further, participants may not be able to accurately recall if they have viewed salient and important political campaign events such as presidential debates (Prior, 2012), and therefore cannot be expected to remember the news media they have consumed.

Alternative approaches to measuring pro-attitudinal media use involve estimating media exposure by measuring the possibility of exposure (Slater, 2004). For example, media attention towards a topic can be measured by content analysis and the aggregate measures can be linked to individual survey responses over many data collection intervals (>30) to estimate effects of exposure (e.g. Gonzenbach, 1996; Hertog & Fan, 1995; Rogers, Dearing, & Chang, 1991; Trumbo, 1995; Yanovitzky & Bennett, 1999). However, this type of estimation procedure cannot produce a measure of individual exposure, which is necessary to test a mediation between media use and other variables (Slater, 2004). Therefore, this type of estimation procedure of pro-attitudinal media exposure cannot produce the indicator of media use necessary to model the indirect effects I hypothesize in my model.

Therefore, I utilize a self-report of pro-attitudinal media use that likely overestimates total media consumption. However, even though the self-report is not useful to estimate total use, it can still likely be used to to estimate media consumption relative to the others in the sample. Since most people overestimates their media use in self-report measures, then the measure is still able to correctly differentiate between those

who consume a lot of partisan media compared to those who do not and any relationships found between media use and other variables are still likely valid findings. Participants were asked how frequently they normally consume media, on a range from 1 (*Zero times*) to 7 (*Several times a day)*, partisan media including: Fox News, MSNBC, Liberal-leaning websites/blogs, and Conservative-leaning websites/blogs, Republican talk radio (e.g. Rush Limbaugh), and National Pubic Radio (NPR).

The frequency of **political social media communication** is measured by observing the actual communication created by participants, but I also measure how participants use social media with a self-report. Specifically, I adapt the Facebook and Twitter use scales from Warner, Turner-McGowen, and Hawthorne (2012) to suit the Presidential primary data collection context and by expanding the scale to also measure use of the Reddit and Disqus platforms. The scale assesses how likely the participant was to engage in the different types of communication behaviors available on a given platform and how much attention they devoted to a specific event on the platform.

Among each of the following questions assessing how frequently a platform was used to communicate about the Presidential primaries, respondents answered using a scale ranging from 1 (*Very Unlikely*) to 4 (*Very Likely*). Regarding their Facebook use participants indicated how likely each participant was to see information regarding the primaries on their news feed, read a link or watch a video posted to their news feed regarding the primaries, see friends discussing the primaries, post a comment about the primaries, "like" a status posted about the primaries, and to post a status about the primaries. Also, participants indicated how likely they were to use Twitter to see information about the primaries on their feed, to follow a link they saw on their feed

about the primaries, to see friends or acquaintances tweeting about the primaries, to retweet information about the primaries, to favorite a tweet discussing the primaries, and to personally tweet about the primaries. I also assessed if the participants were likely to use Reddit to see information about the primaries on their front-page, to follow a link they saw on their front page about the primaries, to read comments that people have made about the primaries, to post a link about the primaries, and to discuss a link about the primaries. I assess how likely participants are to engage with news websites by asking about reading information about the primaries on a news website(s), commenting on a story about the primaries on a news website(s), and reading others comments on a story about the primaries. I did not ask about the use of Disqus directly since Disqus is a platform that is embedded on news websites and therefore may not be recognizable to the participants. Further, each participant was asked how much attention they paid to the primaries on Facebook, Twitter, Reddit, and news websites utilizing response options including: *A lot of attention*, *Some attention*, *A little attention*, and *No attention*. In this analysis, all the items in the political social media use scales were scored so that more attention and engagement was at the top of the scale.

A measure of democratic participation is used as an indicator of **non-violent political engagement**. Mutz (2002) utilizes a summative participation index measuring both confrontational and non-confrontational political participation that might be adapted for this purpose. The original scale includes two items to measure confrontational engagement including: "During the recent campaign, did you talk to any people to try to convince them why they should vote for or against a particular candidate?" and "Did you work for any political party or candidate in the recent election campaign?" Three items

are necessary to estimate a latent construct, and therefore I propose to add "Did you share content online to persuade people to vote for or against a particular candidate?" to the scale. The original scale utilized three items to measure non-confrontational participation including: "Did you attend any meetings or election rallies for any candidate or political party?", "Did you put up a political yard sign or bumper sticker or wear a campaign button for any candidate or political party?", and "Did you give any money to a political party or candidate?" The response options on the original summative scale were expanded to four items ranging from 1 (*Very Unlikely)* to 4 (*Very Likely*) and a statement was added instructing participants to assess their likelihood of engaging in each activity at the beginning the scale.

To measure **political violence,** I have designed and validated a new scale that assesses communicative and physical violence using thirty items modeled as two second-order factors. In my previous research on political violence, I have utilized a measure of the **acceptance of political violence** (APV) that measures agreement with statements indirectly stating that violence was positive or necessary (Hawthorne, 2013; Hawthorne & McKinney, 2013; Hawthorne & Warner, 2013). In the APV measure participants indicated how much they agreed, on a range from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*), with the following statements: "If elections don't fix America's problems, we may need to pursue 2nd Amendment remedies"; "The tree of liberty needs to be nourished with the blood of revolution"; "If we can't find a peaceful solution to the problems facing America, true patriots may need to take matters into their own hands"; "When politics fail, violence is sometimes necessary", "I can see why some people support violent revolution"; and "I can for see a day when violent measures may need to be taken to

protect the United States form itself." While performing adequately, there are room for improvements with the APV measure. For example, the content domain of APV does not cover the whole broad content domain of political violence that includes both communicative and physical components. Further, the wording of some of the items may be interpreted differently based on existing political involvement or political knowledge because of their allusions to current politics (i.e. 2nd Amendment remedies and referencing a quote from Jefferson).

Given these issues, in this project I develop a new measure of political violence that might be more suited to a general sample and that covers a broader content domain of violent behavior. Measuring political violence is difficult for several different reasons, implying that there are several threats to the validity of a political violence scale. I elaborate on the threats to validity presented by measuring political violence and the design steps that provide evidence for the validity of the scale below.

Designing a Measure of Political Violence

Any participant who refuses to answer questions assessing political violence because they, in truth, are potentially willing to engage in political violence introduces data that is missing not at random (see Myers, 2011 for a review on missing data). There are no reliable techniques to impute data that is missing not at random (Schafer & Graham, 2002), and therefore this situation presents a missing data problem that can bias results. Further, participants may artificially reduce their scores on a scale asking directly if an individual will engage in political violence in order to satisfy the perceived pro-social expectations of the researcher and/or society, or otherwise stated the social desirability biases of the participants may introduce error into observations. People may

also be unable to accurately assess their likelihood of engaging in political violence because such information may not be cognitively accessible. Each of these potential issues could introduce error that threatens the validity of a political violence measure.

Through careful design, the error associated with self-report measurements can be minimized. Measurement design is a reciprocal process that utilizes assessment of the measurement to improve the overall measure performance. This rigorous assessment and modification process can produce substantial amounts of evidence supporting the validity of a self-report measure.

The field of psychometrics has developed specific techniques to establish evidence of different types of validity for self-report measures. There have been debates in the psychometric literature regarding the best methodological techniques to find evidence of validity and the most important indicator of validity (e.g. Borsboom, Mellenbergh, & van Heerden, 2004). I view validity as a construct that can be measured using multiple indicators and to get a more complete view of the validity of a construct one should gather evidence supporting claims about the different types of validity. In this project, I gather evidence supporting the content and construct validity of the political violence measure throughout the measure design process.

Measure Design and Item Creation. A person makes a decision to commit political violence, and the decision is made using information processing shortcuts. Expressing opinions and positions in politics is at times a gut reaction prompted by information processing shortcuts that people attempt to rationalize later (e.g. Lodge & Taber, 2013). A self-report of political violence might measure opinions about violent political engagement rather than asking about political violence directly in order to

ameliorate some of the error introduced by missing data, social desirability bias, and cognitive inaccessibility. The specific responses that are expressed by participants when asked about their positions on political violence may be influenced by the same type of information processing shortcuts as the decision to commit political violence, implying that any relative differences found in a scale measuring attitudes about political violence may covary with the true likelihood of the individual to commit political violence. Fishbein and Ajzen (1975) show that whether someone engages in a specific behavior is related to evaluations of the behavior (on a general positive/negative dimension) and the perceived subjective norm regarding the behavior. Ajzen (1991) subsequently showed that both evaluations of a behavior and subjective norms, as well as perceived behavioral control, or self-efficacy associated with a behavior, explain a significant amount of variance whether someone actually engages in a target behavior.

Therefore, assessments of evaluations, perceived social norms, and behavioral efficacy associated with political violence can be utilized as an indicator of the relative likelihood associated with violent political engagement. However, such a relative indicator of political violence cannot and should not be used as an absolute indicator of political violence. This all goes to say that the scale I am designing can measure relative differences among a sample of people but it cannot detect whether a person will or will not commit political violence.

My broad definition of violence implies that two large factors make up the content domain of political violence that range in intensity from communicative to physical violence. Communicative violence is related to engaging in verbal and non-verbal incivility such as name calling, harsh and unnecessary characterizations,

threatening comments, rude gestures, and other verbal behaviors aimed to inflict physical or emotional harm. Physical violence is related to engaging physical behaviors, with the body (i.e. punches and kicks) and with weapons, aimed to inflict physical or emotional harm. Physical violence is a more intense form of engagement than communicative violence and within each of these large intensity factors, sub-factors made of questions address the evaluations of the behavior, the perceived subjective norm of the behavior, and the self-efficacy associated with the behavior.

A total of 96 items were written that systematically sampled from the entire content domain describing political violence. Systematic sampling from the content domain of a construct implies that the initial item pool is broad and more comprehensive that one's theoretical view of the target construct and should include content that is ultimately shown to be tangential or unrelated to the given construct (Clark & Watson, 1995). Statistical tests can test if an item in a scale is underperforming and the item can be removed, but it is impossible for any test to detect content that should be in the measure that is missing. Good item writing practices such as writing items that are single-barreled, simply worded, and phrased to only address the target construct (Clark & Watson, 1995), were utilized in this stage. See Appendix 2 for a set of preliminary items measuring political violence.

Content Validity. Content validity refers to the extent that the items in a measure are "relevant to and representative of the targeted construct for a particular assessment purpose" (Haynes, Richard, & Kubany, 1995, p. 238). Therefore, to achieve content validity all of the items on a measure must be relevant to the target construct and must be representative of all of the factors of a target construct. "During initial instrument

development, the purpose of content validation is to minimize potential error variance associated with an assessment instrument and to increase the probability of obtaining supportive construct validity indices in later studies" (Haynes et al., 1995, pp. 243–244).

To gather evidence of content validity the full instrument measuring political violence, including instructions, all items, and response options was distributed to a panel of experts for quantitative rating and qualitative feedback (Haynes et al., 1995). This feedback as then analyzed and suggested changes in the scale were be implemented. I review the results of this analysis in chapter four, but you can find the revised scale in Appendix 3.

A panel of expert judges was recruited via email to evaluate the measure of political violence. Experts that study violence, political behavior, social psychology, and political communication were specifically targeted for recruitment because of the relevance of their expertise to the processes being measured. Table 1 contains a list of potential members of the panel of experts. A total of 7 of these judges anonymously responded and offered their feedback on the scale.

Table 2

Panel of Experts

Name, Institution; N = 34
Alan I. Abramowitz, Emory University
Craig A. Anderson, Iowa State University
Kevin Arcenaux, Temple University
Jamie Arndt, University of Missouri
Mary Banwart, University of Kansas
Cassandra Bird, University of Kansas
Josh Bolton, University of Missouri
Brad J. Bushman, The Ohio State University
Dianne Bystrom, Iowa State University
Heesook Choi, University of Missouri
Calvin Coker, University of Missouri
Richard Felson, Pennsylvania State University
Morris P. Fiorina, Stanford University
R. Kelly Garret, The Ohio State University
Jeff Greenberg, University of Arizona
Molly Greenwood, University of Missouri
Shanto Iyengar, Stanford University
Freddie Jennings, University of Missouri
Martin Johnson, University of California, Riverside
Eva Jonas, University of Salzburg
Mike Kearney, University of Kansas
Matthew Levendusky, University of Pennsylvania
Mitchell S. McKinney, University of Missouri
Markus Prior, Princeton University
Tom Pyszczynski, University of Colorado, Colorado Springs
Dhavan Shah, University of Wisconsin
Sarah Smith-Frigerio, University of Missouri
Sheldon Solomon, Skidmore College
Mary Sorenson, University of Missouri
Esther Thorson, University of Missouri
Kjerstin Thorson, University of Southern California
Benjamin R. Warner, University of Missouri
Kelly Winfrey, Iowa State University

At the beginning of the survey the experts were briefed about the measure design and the definitions of violence utilized. Judges were instructed to rate the items, the factors, and the measure as a whole in reference to several criteria on scales ranging from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*). The battery of items that judges responded to was derived from the elements of content validity outlined by Haynes and colleagues (1995) (see Table 2 and Appendix 3 for further descriptions and the items specifically used). Further, each judge was be prompted to provide qualitative feedback for the items and scale overall (Haynes et al., 1995). Judges were exposed to the items in six different groups organized by the type of attitude being assessed by the group (evaluations, perceived social norms, and self-efficacy associated with both communicative and physical violence). Each part of the scale that the judges were assessing were present on the screen when the assessment was made, implying that judges did not have to recall any part of the scale to respond to the questions. The results were analyzed by calculating aggregate measures and items.

Table 3

Elements of Content Validity and Item Battery

Element	Scope	Question
The array of items selected is representative of content domain	Overall	The array of items selected is representative of content domain of the target construct.
Instructions to participants	Overall	The instructions to participants are appropriate.
Coverage of violence targets sampled	Overall	The different situations described in the scale cover the domain of situations that are relevant to the target construct.
Coverage of violent behaviors sampled	Overall	The different behaviors described in the scale cover the domain of behaviors that are relevant to the target construct.
Components of are part of a larger factor	Factor	The individual items within the factor are appropriately combined into the factor.
Precision of wording or definition of item	Item	The language used in the item is precise (has only one meaning in the context of question).
Item response form	Item	The item response form is appropriate for the item.

Note: Elements described from Haynes et al., 1995

Item Selection Process. To select the best items from the scale it is necessary to have participants answer all of the potential items on the scale. Once data has been collected various statistical techniques can be utilized to find the items on the scale, which will maximize construct validity (which is formally tested at a later step). There is some disagreement in the literature regarding which criterions should be utilized to select items. For example DeVellis (2011) argues that items should be selected based on their inter-item correlations. Focusing on maximizing the inter-item correlations in a scale privileges the reliability of the scale as the criterion for determining the best items on the scale. However, the most common metric of reliability, Cronbach's Alpha, is a function of the inter-item correlations and the length of the scale (Schmitt, 1996), implying that

utilizing reliability to select items may result in long scales that artificially inflate estimates of reliability.

Alternatively, Clark and Watson (1995) and Smith and McCarthy (1995) argue that the unidimensionality of the factor should be the criterion to judge whether an item fits in the scale. Unidimensionality implies that each item is primarily related to other items in the factor and is less related to items outside of the factor. This approach privileges discriminant and convergent validity, which are components of construct validity, as the criterion for selecting items. Therefore, items were selected to maximize the unideminsionality of the scale rather than just focusing on inter-item correlations and the reliability of the scale.

Pilot Sample. A separate sample was recruited on February 8, 2016 to test all of the items on the political violence measure and perform item selection analyses utilizing Amazon mTurk. Other variables were also included at this data collection time point in order to pilot test the measures and to test construct validity on two independent samples. Early research on Amazon mTurk suggested the demographics of workers were diverse, but not representative of any large country-based population (Ross, Irani, Silberman, Zaldivar, & Tomlinson, 2010). However, the Amazon mTurk worker market has changed, and now there is a set of professional mTurk workers, and as a result the demographics of the worker population have shifted (Silberman, Milland, LaPlante, Ross, & Irani, 2015). There currently are no good estimates of the demographics of the Amazon mTurk worker population. Therefore, it is necessary to utilize qualifications on this research project to recruit participants within the target population. Given that this project

concerns U.S. politics and political behavior, U.S. citizenship and being at least 18 years of age, were required qualifications.

Each worker was compensated $2.00 through the Amazon mTurk system for their time and on average workers completed the survey in 38 minutes and 22 seconds. A total of 200 participants were recruited, but four cases (2%) were deleted due to drop-offs and failed attention checks, leaving an effective sample size of 196. The sample was middle aged (M = 35.67, SD = 10.14) and predominantly male (57.14%, n = 112; female: 40.82%, n = 80). In regards to race and ethnicity, most of those in the mTurk sample identified as White (82.14%, n = 161), though others did identify as Asian (6.63%, n = 13), Hispanic/Latino (4.59%, n = 9), and Black (4.08%, n = 8). In aggregate the sample leaned towards the Democratic party (M = 3.33, SD = 1.58) and was slightly liberal (M = 3.26, SD = 1.65).

Item Selection Analysis. This data is utilized to select items that perform well for the political violence scale. There are several metrics and analyses that are utilized to examine how the items work together as factors including inter-item correlations, exploratory factor analysis, and confirmatory factor analysis. Items were selected with moderate inter-item correlations and that maximize the unidimensionality of each factor. First, those items with fewer inter-item correlations than others at the .40 level were removed (there are no set rules for when inter-item correlations are to low and therefore the distribution of correlations among the items was utilized and .40 was one standard deviation below the mean of all inter-item correlations implying that .40 is a low correlation). Among the remaining items, exploratory factor analysis is used to find the initial factor structure, using criteria related to the number of factors it takes for

associated eigenvalues to exceed one and to explain at least 50% of the variance to find the number of factors in the scale and a 60/40 loading/cross-loading criteria for selecting the items that load onto the factors (Allen, Titsworth, & Hunt, 2009). The remaining items and factors were then fit into a confirmatory factor analysis (CFA) model. Items that cross-load onto other factors, that cross-load onto items in other factors, and the cross-load onto other items in the same factor at a greater than .10 level were removed to improve overall model fit. Model fit for the CFA is evaluated using the ML χ^2, the Tucker-Lewis/non-normed fit index (TLI/NNFI), the comparative fit index (CFI), and the root mean square error of approximation value (RMSEA). The results of the item selection analysis are reviewed in Chapter 4.

Modeling Political Violence. In this analysis each of the factors of the political violence scale are scored so that high scores indicate more positive opinions about political violence and low scores correspond to more negative opinions about political violence. Each of the opinions about political violence, including evaluations, perceived social norms, and perceived behavioral efficacy, create sub-factors related to political violence. Each of the sub-factors was then used to model the larger communicative and physical violence factors using a second-order model. In a second order model, each item loads onto a lower-order construct, and then those lower-order constructs then load onto the primary constructs. This modeling approach assumes that the "common variance among the indicators associated with the primary, overarching […] factors can be adequately captured in the correlations among the lower order constructs" (Little, 2013, p. 372). The primary communication and physical violence constructs are used in the model to explore relationships with other variables.

Construct Validity. At its core, construct validity refers to the extent to which a measure is correlated with measures of similar or related constructs and the extent to which a measure is not correlated with different constructs (Cronbach & Meehl, 1955). In other words, construct validity refers to the extent that a measure converges with similar constructs and can discriminate between different constructs. Evidence of the construct validity of a measure can be gathered by testing a nomological network of relationships between the construct in question and other related and different constructs (Cronbach & Meehl, 1955). I test the construct validity of the self-report measure by showing that my measure of political violence predictably relates to other self-report measures. The set of relationships outlined in my theoretic model, scales that I worked with in previous research on political violence (APV), and in previous research on violent behavior, are summarized in Table 3 and are utilized as a nomological network.

Table 4

Predicted relationships with political violence

Variable	Direction
In-group Bias	Positive
Political Trust	Negative
Pro-Attitudinal Media Use	Positive
Frequency of Political Social Media Use	Positive
Positive Authored Comm.	Negative
Acceptance of Political Violence	Positive
Age[a]	Negative
Sex (0 = Female; 1 = Male)[a]	Positive

Note: a = see C. A. Anderson & Bushman, 2002

Analysis of Construct Validity. The nomological network was evaluated using structural equation modeling (SEM) with ML estimation using lavaan (Rosseel, 2012), a package for the R statistical software suite (R Core Team, 2014). SEM was selected for this analysis because it allows for the simultaneous estimation of the covariance paths that make up a nomological network to estimate construct validity (Eid, Lischetzke, & Nussbeck, 2006). To estimate the nomological network and in order to verify the quality of measures, I utilize confirmatory factor analysis (CFA) and the estimate the covariances of relationships between variables.

Model fit for the CFA is evaluated using the ML χ^2, the Tucker-Lewis/non-normed fit index (TLI/NNFI), the comparative fit index (CFI), and the root mean square error of approximation value (RMSEA) and the square root mean residual (SRMR).

Values above .90 for the TLI/NNFI and CFI indicate the model has adequate fit (Marsh, Hau, & Wen, 2004). RMSEA and SRMR values below .10 indicate adequate model fit while values below .08 are considered acceptable model fit (Little, 2013). Significance of covariance paths was assessed by constraining each path one at a time to zero and checking for the difference in χ^2 model fit statistics (Eid et al., 2006).

Observing Political Social Media Use

During the main survey portion of the project, participants log into and provide access to the content they have produced on the Facebook, Twitter, Reddit, and Disqus platforms. The increasing amount of unstructured data available from the Internet produced naturally by people on platforms like Facebook, Twitter, Reddit, and Disqus presents a treasure trove of data that can inform research. Some have argued that this big data has the potential for making the standard social scientific process – the null hypothesis test – obsolete (C. Anderson, 2008). Regardless of whether the null-hypothesis test becomes obsolete, big data may change the way researchers think about science and error control in statistical inference.

The null hypothesis test is based on finding evidence that falsifies a preconceived hypothesis that a relationship does not exist between two variables (Krantz, 1999). The null hypothesis test controls for Type I error, or error derived from claiming a relationship exists when none really exists, through the use of the *p*-value criterion for statistical significance (Cohen, 1994). While null hypothesis testing controls for Type I error it does not control for Type II error, or error derived from claiming a relationship does not exist when a relationship actually exists. This imbalance in error control implies that null hypothesis tests may be systematically biasing the results of scientific inquiry

and causing false-negative interpretations of relationships that actually exist (F. L. Schmidt, 1996).

The most sophisticated algorithms for summarizing text data are entirely data driven, meaning they find all the relationships that exist between the words and other markers within the data set (Schwartz & Ungar, 2015). Probing for the relationships in a dataset has been characterized as data mining, and sacrifices Type I error in favor of minimizing Type II error. "Nonetheless, from a policy perspective, these systematic predictive and analytic techniques can provide insight into, if not directly solve, significant social problems" (Shah, Cappella, & Neuman, 2015, p. 9). The main concern of data mining is engineering a better solution to a specific problem, rather than developing better scientific knowledge (J. Lin, 2015).

I incorporate the tools of data driven big data analysis in order to explore how communication content is related to political attitudes and engagement. However, I also utilize a dictionary based coding scheme to characterize content that exists within the data set. I review the specific algorithms utilized in both of these analysis schemes below. *WordStat*, a program developed by Provalis Research, that is an extension to the qualitative data analysis program *QDAMiner*, is utilized to conduct this analysis (Provalis Research, 2014). However, first I elaborate on the social media data sources and the text data preparation.

Data Sources

Data will be collected from the Twitter, Facebook, Disqus, and Reddit platforms utilizing publicly accessible application programming interfaces (APIs). A significant portion of the online population utilizes one or more of these four platforms, though they

skew heavily towards a Western audience. Each of these platforms is different in important ways. All together 49.63% of participants (n = 134) provided access to at least one of their social media accounts, and a total of 83,864 pieces of content were collected from these accounts.

Twitter is a micro-blog and allows status updates of 140 characters or less. Twitter has become a place where both the public and elites can discuss political events together in a real-time fashion (Ampofo, O'Loughlin, & Anstead, 2011; Anstead & O'Loughlin, 2011; Hawthorne, Houston, & McKinney, 2013). Twitter is used by 23% of online adults and the user population is skewed towards adults under the age of 50 and that are college-educated (Duggan et al., 2015). Structurally Twitter is a communicative space characterized by unidirectional subscriber behavior (e.g. one-way subscription to content), strings of conversations marked by a hashtag (#), directed conversation (@replies), and retweeting behaviors that function to spread and organize content (Halavais, 2013). At the time of data collection, the Twitter API is rate limited, such that only a weeks worth of social content from each platform could be downloaded. A total of 33.95% (n = 90) of the sample provided access to their Twitter account and a total of 1,733 tweets were collected from these participants.

Facebook is a social network with bi-directional subscriber behavior (e.g. mutual subscription to content), and several communication behaviors including public wall posting, commenting and private messaging. A total of 71% of online adults used Facebook in 2014 (Duggan et al., 2015). Women are more likely to use Facebook than men and Facebook use is growing among Internet users 65 and older (Duggan et al., 2015). The entire history of a users Facebook posts was available for download from the

platform. A total of 32.22% (n = 87) of the sample provided access to their Facebook account and these participants produced a total of 81,967 Facebook posts.

Reddit, the self-proclaimed front-page of the Internet, is a website where users submit, vote rank, and discuss web-content links or text posts. As of June 2015, Reddit has over 172 million unique visitors per month (Reddit Inc., 2015). Approximately 6% of all online adults are Reddit users (Duggan & Smith, 2013). The entire history of Reddit posts by users were available for download through the platform, though it is possible for users to delete all of the content they have posted easily (by selecting all posted content and deleting it on one page summarizing posts made to the platform). A total of 1.85% (n = 5) of the sample provided access to their Reddit accounts and a total of 164 comments on Reddit were collected.

Disqus (pronounced as discuss) is an application that is included on webpages to provide an in-page comment section. Users that register within the centralized Disqus framework, can comment on pieces of content around the web, and find new pieces of content through the Disqus network. Disqus is utilized on 75% of websites that use a third party commenting system and receives over 500 million unique visitors in a month (danielha, 2011). Some of the biggest websites that use Disqus to power their comment system include CNN.com, Politico.com, and NPR.com. No one in the sample provided access to their Disqus account and so no data was downloaded from this source for use in this analysis.

Data Filtering and Pre-Processing

The text content produced by participants in their Facebook posts/comments, Tweets, and Reddit comments may use different inflections to refer to the same words,

may include typographic errors, and use slang that could bias results. Therefore, pre-processing must be utilized to clean the textual data. Also, the data collection APIs return every post that the user makes on the platform. This could return content that is not related to politics or a user's political views. Unrelated content should be filtered out of the body of text because content features (sentiment and subjects) unrelated to politics, that may not be related to participant political attitudes. Therefore, inclusion of unrelated content may overestimate the occurrence of content features that would impact the estimates in the model. Filtering the captured content to find content that is relevant is necessary to reduce measurement error in the content analysis results.

In order to pre-process the data, I utilize a basic "stop list" of commonly used words (such as articles) so that those words do not influence the analysis or results. I also utilize a lemmatizer, to group together the same words that utilize different inflections (e.g. plurals and singular versions of nouns, differently conjugated verbs). To find content that is relevant to politics a list of all words used in the dataset was compiled and this this list was searched for any words that were clearly associated with politics. However, very few words could be clearly associated with politics and the overall frequency of these words was low, so this approach was abandoned.

A weighted selection approach using some self-report variables from the survey data was then employed to find content that was more likely to be political than the remaining content. Specifically, correlations were calculated between the self-report measures associated with discussion of the Presidential primaries on Facebook, Twitter, Reddit, and news websites and the frequency of every word used by participants. Higher correlations of words with the self-report measures imply that the specific words were

used frequently by those who said they talked about politics online, and therefore the content including these words is more likely to be political than other content. Any word that was correlated at a .10 level with self-report discussion of politics over social media was included in a "go list" (see Appendix 5 for the go list). Any piece of authored content that contains any single keyword in the go list is filtered into this analysis. A total of 31.11% of participants (n = 84) used one of the words indicating that their content was more likely to be political than other pieces of content and these participants produced a total of 27,035 political social media posts (318.05 posts per participant).

Content Features

One of the most prominent content features that I examine is the **frequency of posts** that are more likely to be about politics. This count based variable provides an indicator of the amount of political talk the participant engages in. There are a variety of algorithms that enable more complex analyses and summarizations of a body of text. For example, human defined dictionaries can be used to code content by measuring if specific words are included. Data-driven techniques calculate the strength of relationship between words to find content that commonly occurs together. "Hand-driven techniques [such as dictionaries] tend to be more accessible, theory-driven, abstract, and able to handle small datasets, while data-driven [techniques] tend to be more transparent, capture more connections, and are able to yield unexpected associations" (Schwartz & Ungar, 2015, p. 80).

Manual human driven approaches to computational analysis generally involve the creation of custom dictionaries that categorize words. Several existing dictionaries have been developed by researchers for a specific purpose or generated by crowdsourced

ratings of specific words (Schwartz & Ungar, 2015). I predict that the use of positive or negative sentiment in political social media is related to the in-group bias and political trust. There are several different dictionaries that have been utilized to code the emotionality or sentiment in text oriented towards both broad valence emotions and specific feelings.

To code for **positive and negative sentiment**, I utilize a broad sentiment coding dictionary, called the Lexicoder Sentiment Dictionary (LSD) (Young & Soroka, 2012a). The LSD is a 4,567 word lexicon constructed to measure the positive or negative affect in the language of political news that has been validated against manually coded and predictive models (Soroka, Young, & Balmas, 2015). The LSD has been utilized in a number of studies to examine how sentiment is utilized in the reporting of political news (e.g. Fournier, Cutler, Soroka, Stolle, & Bélanger, 2013; Soroka, 2012; Soroka et al., 2015).

Data driven approaches to computational analysis seek to summarize and represent the relationships between words within a body of content. Data driven approaches to analysis take the form of either *supervised learning* methods, in which the analysis is directed towards finding a relationship that maximizes or minimizes a specific relationship with an associated variable, or *unsupervised learning* methods, in which words or symbols that tend to occur together are extracted from the text (Schwartz & Ungar, 2015). This project seeks to utilize both supervised and unsupervised learning methods to select relationships that are important. Utilizing supervised learning methods this project finds the subjects referenced in content that are highly related to outcome variables of interest, including in-group bias and political trust. Unsupervised learning

methods are used to find subjects that naturally occur most prominently in the data set. Therefore, I produce two slightly different calculations of the subjects that are important in the text that utilize both to model the relationships between content in political social media communication and in-group bias and political trust attitudes.

I utilize the topic extraction tool in *WordStat* to find **subjects** that occur within the social media communication, utilizing a non-hierarchical exploratory factor analysis based algorithm to find keywords that co-occur frequently within bodies of text. Each co-occurrence keyword can be related to more than one subject if it is used frequently in conjunction with many different terms. Each keyword was required to load at ≥.40 to be considered a meaningful component of the frame. A ≥.40 loading requirement is the default setting in the topic extraction function of *WordStat*. In factor analysis most scholars consider a ≥.40 loading onto a factor as high, while loadings ≥.30 are considered average (Hair, Anderson, Tatham, & Black, 1995), implying that a .40 loading is a conservative criterion of co-occurrence. Each individual piece of content (e.g. a tweet, a post, or a comment) is utilized as a unit of analysis and co-occurrence of words was calculated within the piece of content. When conducting the supervised analysis, the program found the subjects that are correlated with in-group bias and political trust self-report variables. These results show what subjects in the social media content are associated with scores on the survey self-report variables.

The unsupervised portion of this analysis produced many subjects, of which a few were selected manually based on how frequently they were used. The algorithm was utilized to extract 100 total topics from the body of authored content. The top ten subjects

that are able to characterize the most pieces of social media content were selected for further use to model the relationships in question.

Due to differences in the amount of historic content that could be downloaded from each platform and individual differences in the length of time that participant's have held accounts on platforms, the amount of social content is not evenly distributed across participants. Therefore, I standardize each of the observed social variables by time in order to control for differences the amount of content each participant posted. Specifically, the standardization produced an average occurrence of a subject or sentiment for each participant that excluded the days that the participant did not post. The frequency of each content analysis variable (the use of a subject or sentiment) was calculated on each day the individual participant posted and the sum of the frequencies was divided by the amount of days on which the participant posted. Functionally, this means that if a person posted on only one day with only one use of positive sentiment, then their score for positive sentiment is 1.00, and that if another person posted on 100 days with 50 uses of positive sentiment, then their score for positive sentiment is .50. When used as a variable, the standardization process produces an indicator of the relative use of each content feature within each participant's posted content. Further, because a large amount of social content was retrieved from Facebook and comparatively only a small amount content was downloaded from Reddit and Twitter, the content is collapsed together such that posts on each platform are treated the same way rather than estimating the individual relationships with each platform.

Collecting Evidence of Validity

By showing how these content analysis methods triangulate with scores on self-report variables in a predictable fashion, I can provide evidence for the validity of the content analysis observations (Campbell & Fiske, 1959). Krippendorff (2013) argues that predicting and testing the relationship between content analysis variables and variables gathered by other methods through correlative and predictive models produces evidence supporting the results of the content analysis. The relationships outlined in Table 4 are predicted by my theorizing of the role of communication behaviors with in-group bias and political trust, and include some measures of the same constructs using different methods.

Table 5

Predicted relationships with social media communication

Variable	Social Media Metric	Direction
In-group Bias	Frequency of Posts	Positive
Political Social Media Use	Frequency of Posts	Positive
Political Trust	Negative Sentiment	Negative
Political Trust	Positive Sentiment	Positive

Main Survey Participants

A convenience sample of college-aged students was recruited from a large Midwestern university to participate in this project. A convenience sample was utilized in this project because participation required participants to identify themselves via their social media accounts, which is against the terms of service of most third-party

companies that recruit and manage representative samples of participants. A total of 760 potential participants were recruited for this project and 308 participated (40.53% of the potential sample). From those that participated, 38 (12.34%) cases were deleted due to drop-offs and failing attention checks, leaving an effective sample size of 270.

Recruitment was conducted for two weeks, between 3/7/16 and 3/18/16. The Presidential primary in the state were recruitment was conducted was held on 3/15/16, well within the window that recruitment occurred, implying that this may have been a time of heightened political participation and attention to politics among the sample. The sample was predominantly college aged (M = 20.66, SD = 1.30) and mostly consisted of women (64.07%, n = 173; male: 35.56%, n = 96). The sample also predominantly identified as White (78.52%, n = 212), though those that identified as Black (10.37%, n = 28), Asian (3.33%, n = 9), Hispanic/Latino (2.96, n = 8), or another race/ethnicity (4.81%, n = 13) were also represented in the sample. In aggregate, the sample leaned slightly towards the Republican party (M = 3.98, SD = 1.68) and was slightly conservative ideologically (M = 3.81, SD = 1.69).

Data Organization and Analysis

The self-report survey measures were linked to content analysis results of the social media content produced by each individual participant. However, given the relatively low number of participants that engaged in political talk, the analyses involving the observed social media variables is conducted using a separate analysis strategy than the self-report data. The self report data is modeled utilizing structural equation modeling (SEM) with ML estimation using lavaan (Rosseel, 2012), a package in the R statistical software suite (R Core Team, 2014). SEM is selected for this analysis because it corrects

for measurement unreliability, enables the simultaneous estimation of multiple independent and dependent variables, and the estimates the relationships between those variables (Brown, 2006; Kline, 2011). Self-report measures are utilized to calculate latent constructs within the tested models. In the main survey data, latent variables for which there are several (more than four) indicators are calculated using correlational parceling, a procedure that averages together the indicators that are most strongly related within a construct, to create models that are locally just-identified (having three indicators per construct) and which has several psychometric and model estimation advantages over calculating latent constructs with individual items (Little, Rhemtulla, Gibson, & Schoemann, 2013). To estimate a model, first a measurement model was fit utilizing confirmatory factor analysis (CFA) and upon achieving adequate levels of model fit a structural model was fit to test the relationships (Kline, 2011). Given that the political trust variables each cover a different portion of the political trust content domain and are highly related, the political trust variables are combined into a second-order political trust latent construct in the same way that the political violence sub-factors were combined into the larger communicative and physical political violence latent constructs.

Model fit for the CFA was initially evaluated using the ML χ^2, the Tucker-Lewis Index/non-normed fit index (TLI/NNFI), the comparative fit index (CFI), the root mean square error of approximation value (RMSEA), and the square root mean residual (SRMR). Values above .90 for the TLI/NNFI and CFI indicate the model has adequate fit (Marsh et al., 2004). RMSEA and SRMR values below .10 indicate adequate model fit while values below .08 are considered acceptable model fit (Little, 2013). Significance of direct regressed pathways was assessed using the χ^2 difference test (Kline, 2011). Also,

95% confidence intervals of the estimates of direct effects were calculated and presented using 10,000 bootstrapped iterations. Indirect paths through a mediating variable were estimated using the product of the standardized estimates of direct paths (Holbert & Stephenson, 2003), and 10,000 bootstrapped iterations were utilized to calculate the 95% confidence interval of the indirect effect estimates to test if each estimate is significantly different from zero.

The predicted relationships between observed social media variables and the relevant self-report variables, political trust and in-group bias, are analyzed using linear and generalized linear models, depending on the criterion variable. All of the observed variables measuring political trust are continuous along a relatively small bounded range (e.g. -1 – 1, 1 – 7) and I assume responses on these variables are normally distributed along the range. The indicator of in-group bias, however, has a very large potential range (0-100), uses only integers to score responses, and there is the potential for a many responses at the high end of the scale. Therefore, in-group bias is unlikely to follow a normal distribution, but rather should be modeled using the Poisson distribution, much like count data.

The relationships between political trust in the self-report data and the observed social media variables will be modeled using multiple regression, with several other self-report variables used as controls including age, sex, and pro-attitudinal media use. In multiple regression contexts the coefficient associated with each predictor is a linear estimate of independent relationship between the predictor and the dependent variable. The relationships between in-group bias in the self-report data and the observed social media variables will be modeled using a generalized linear model of the Poisson

distribution and, similarly, several other variables from the self-report data including age, sex, and pro-altitudinal media use are used as controls in the model. The individual coefficients associated with predictors in a Poisson regression model are generally interpreted as the percent change in the dependent variable with one change in increment of the independent predictor (Smithson & Merkle, 2014)

Conclusion

In this chapter I have outlined my methods to test the relationships between communication behaviors, political trust, in-group bias, and political engagement. The measurement of political violence and online communication behaviors present unique methodological issues, which I address through the validation of my self-report and quantitative text analysis steps. An overview of the variables that make up the data I have collected is presented in Table 5. In chapter four I review the results associated with this methodological plan.

Table 6

Overview of Variables

	Main Survey			Pre-Test Survey		
Variable	***M***	***SD***	**α**	***M***	***SD***	**α**
Specific Political Trust	3.47	.93	.88	2.76	1.17	.94
Threat Factor	3.98	1.02	.79	3.60	1.25	.84
Diffuse Political Trust	1.57	.45	.57	1.41	.48	.75
Threat Factor	2.12	.39	.67	2.10	.44	.73
In-Group Bias	73.18	55.93	-	84.67	56.45	-
Pro-Attitudinal Media Use	2.04	1.11	.67	1.99	.94	.59
Political Social Media Use[SR]						
Facebook	2.35	.73	.87	2.27	.83	.90
Twitter	2.14	.93	.93	1.75	.84	.93
Reddit	1.11	.55	.94	1.60	.81	.93
News Websites	2.12	.76	.82	2.50	.74	.82
Freq. of Social Media Posts[O]	1.87	1.60	-	-	-	-
Social Media Sentiment[O]						
Positive Sentiment	.98	.78	-	-	-	-
Negative Sentiment	.61	.55	-	-	-	-
Non-Violent Pol. Engagement						
Non-Confrontational	1.61	.71	.80	-	-	-
Confrontational	1.91	.76	.71	-	-	-
Acceptance of Political Violence	2.97	1.83	.82	-	-	-
Political Violence						
Communicative Violence	2.66	.88	.89	2.35	.93	.91
Evaluations	2.28	1.19	.90	2.29	1.22	.85
Perceived Norms	3.41	1.11	.78	2.71	1.17	.89
Behavioral Efficacy	2.32	1.04	.85	2.04	1.17	.93
Physical Violence	1.85	.87	.90	1.55	.70	.90
Evaluations	1.66	1.00	.96	1.54	.94	.90
Perceived Norms	2.03	1.02	.83	1.58	.70	.88

Note: [SR] Self-Report Variable; [O] Observed Variable; Mean and standard deviation are calculated using simple aggregates of indictors associated with the variables; α refers to Cronbach's Alpha; Spaces filled with a dash (-) indicate that the variable was not collected at the specific data point or is not applicable to the given measure.

Chapter 4: Results

In this chapter I present the results of my theoretic model, hypotheses, and research questions outlined in chapter two that are derived from the methods that I outlined in chapter three. However, I begin by reviewing the results and intermediate processes associated with developing and validating my measure of political violence. I conclude with some descriptive results from the quantitative text analysis procedures and review the relationships between the observed social media variables and political trust and in-group bias.

Measuring Political Violence

In this section I review the results associated with validating, refining, and modeling the political violence scale. I begin by reviewing the results from a survey of a panel of experts in order to assess the content validity of the scale (Haynes et al., 1995). I then review results associated with selecting scale items, identifying the patterns of relationships between factors of the political violence construct, and modeling the construct. Finally, I present tests of the construct validity of the political violence measure (Cronbach & Meehl, 1955).

Content Validity

The content validity of the scale was rated by a panel of experts recruited from the political communication, political science, and social psychology fields. The experts rated the precision of the item wordings and the appropriateness of response options associated with the original 96 items by viewing the items in six groups of sixteen that were grouped because they addressed the same attitude (evaluations, perceived social norms, and self-efficacy) about the different violence intensities (communicative and

physical). The experts were asked to indicate any issues with individual items within the group and to provide general feedback about the items as a group. Experts then considered the appropriateness of the violence intensity factors (communicative and physical violence), the appropriateness of the instructions to participants, and the representativeness of the sampled violent behaviors and targets from within the political violence content domain.

The aggregate ratings from experts were largely positive, with experts agreeing that the items were precise (overall $M = 5.49$, average $SD = 1.76$), utilized appropriate response forms (overall $M = 5.74$, average $SD = 1.57$). See Table 6 for the group aggregate ratings of precision of items and response form appropriateness. The experts also indicated that the scale utilized appropriate violence intensity factors (Communicative $M = 5.5$, $SD = 1.6$; Physical $M = 5.57$, $SD = 1.72$), contained appropriate instructions for participants ($M = 6.14$, $SD = 1.86$), and representatively sampled targets ($M = 6.14$, $SD = .69$) and behaviors ($M = 5.85$, $SD = 1.46$) from the political violence content domain.

Table 7

Aggregate Expert Content Validity Ratings of each Item Group

	Precision of Items	Response Form Appropriateness
Evaluations of Verbal Violence	4.89 (1.45)	6.00 (.93)
Evaluations of Physical Violence	5.78 (1.86)	5.67 (1.58)
Perceived Norms of Verbal Violence	5.00 (1.80)	5.55 (1.66)
Perceived Norms of Physical Violence	6.00 (1.69)	5.63 (1.68)
Self-Efficacy of Verbal Violence	5.25 (2.05)	5.87 (1.88)
Self-Efficacy of Physical Violence	6.00 (1.69)	5.75 (1.67)

Note: *M* (*SD*); *N* = 8

All of the experts offered some qualitative feedback with their responses, 75% (*n* = 6) offered multiple pieces of feedback, and 37.5% (*n* = 3) offered feedback on more than four spaces in the online survey. The feedback provided by the experts remarked that incivility, harassment, and roughing up may be imprecise descriptions of violent behaviors, that the term true patriots was a bit loaded and referred to a specific political group, that the content domain of the verbal violence factor should be expanded to include non-verbal (gesture based) behaviors, that the items measuring self-efficacy did not wholly tap the content domain associated with self-efficacy (specifically that the items covered perceived ability but neglected perceived effectiveness), and that the items were written in a non-standard form that would unnecessarily increase error variance in responses across the questions.

The qualitative feedback was incorporated into the items in a variety of ways. The term "harassment" was replaced with "showing your middle finger" in the questions to remove the imprecision associated with harassment and to expand the verbal violence factor into a communicative violence factor. Similarly, the term "roughing up" was replaced with "punching" to remove the imprecision associated with the meaning of roughing up. However, the term "incivility" was maintained because it referred to a particular type of angry rhetoric that can be used in the context of politics and given the term's widespread use in the media and by politicians, many in the electorate likely use a common definition of incivility. The questions that addressed the self-efficacy factor were rewritten to more fully capture the belief that individual action would be effective at solving a political problem. The items within each factor were also re-written in parallel to reduce the variance in the final scale associated with different question wordings and in this process the term "true patriot" was removed from the questions. The full scale that was edited based on this outside feedback is in Appendix 4.

Item Selection

The full 96 items in the political violence scale were distributed to a sample of Amazon mTurk workers to provide data for item selection. The overall goal of item-selection was to maximize the unidimensionality and the reliability of the scale. In order to maximize unidimesionality, the correlations between most items should be moderate (Clark & Watson, 1995). Items that are lower than moderately correlated with other items in the scale may increase the likelihood of including content in the scale that is outside of the desired dimension of the scale. Further, the inclusion of items that are not strongly correlated with the construct would lower the reliability of the scale, because reliability is

in part a function of inter-item correlations (Schmitt, 1996). Therefore, as an initial cut of the item pool, I remove items that are weaker than moderately correlated with many other items in the scale in order to ensure the unidimensionality and adequate levels of reliability for the scale.

There are no existing rules governing the cut off points for when moderate correlations become weak correlations and how many of these weak correlations are too many for the scale in the context of item selection. Therefore, I turn to the distribution of correlations between the items in the scale for guidance. The average correlation between the items was .55 and the standard deviation of this distribution of correlation scores was .15. In the context of participant responses to self-report items, I would argue that a score that is one standard deviation below the mean is a low, while those scores within one-standard deviation around the mean are moderate. Applying this same logic to the current context, correlations below .40 indicate that the relationship between two items is weak within the distribution of inter-item correlations. There were a total of 14 items with less than 80 inter-item correlations stronger or equal in magnitude to .40 (>=.40 or <=-.40), and these items were removed from further consideration for inclusion in the scale because the amount of weak inter-item correlations among these items would have threatened the unidimensionality and reliability of the scale.

The remaining 82 items were examined using exploratory factor analysis (EFA). My conceptualization of political violence specifies that the communicative and physical violence factors are related, and therefore EFA models were fit using a principal axis factoring method with promax rotation that assumes that any extracted factors will be correlated (Allen et al., 2009). To find the best number of factors to satisfy a solution, a

model was fit specifying a total of 82 factors. In the resultant model, the eigenvalues associated with each factor dropped below 1.0 after a 15 factor solution. Next a 15 factor model was fit to the data. More than 50% of the variance in the items was explained by six factors in the EFA model that was constrained to fit 15 factors. Given that a six factor solution was the smallest that both allowed the associated eigenvalues to exceeded one and explained greater than 50% of the variance of the model (e.g. Allen et al., 2009), a six factor model was selected and utilized to organize the items in the political violence scale for the next steps in the item selection process.

From the six factor EFA model, items were selected to be included in a factor if the items had at least a .60 loading on the factor and did not have greater than a .40 loading on any other factor (Allen et al., 2009). Based on this rule, one factor from the six factor solution was removed because no items loaded onto the factor at an acceptable and unique level. The remaining 5 factors contained a total of 53 items and were organized around the different attitudes assessing political violence including evaluations of communicative political violence, perceived social norms of communicative political violence, perceived self-efficacy associated with communicative political violence, evaluations of physical political violence, and perceived social norms associated with physical political violence. See Table 7 for the selected items organized into factors with main factor loadings.

Table 8

Selected Item Factor Loadings on 6-Factor EFA Model

	Comm. Self-Efficacy	Physical Social Norms	Comm. Social Norms	Physical Evaluations	Comm. Evaluations
CVS1	.80				
CVS2	.75				
CVS3	-.85				
CVS5	.83				
CVS6	-.92				
CVS7	-.80				
CVS8	.64				
CVS9	-.75				
CVS10	-.82				
CVS11	.84				
CVS12	-.75				
CVS14	.91				
CVS15	-.67				
CVS16	.67				
PVN1		.91			
PVN3		-.69			
PVN4		-.65			
PVN5		-.70			
PVN6		.88			
PVN7		-.75			
PVN8		.69			
PVN9		-.71			
PVN10		-.82			
PVN11		.78			
PVN12		.82			
PVN13		-.83			
PVN14		.74			
PVN15		-.63			
CVN2			.80		
CVN3			-.76		
CVN5			.66		
CVN6			-.69		
CVN7			.75		
CVN9			-.74		
CVN10			.74		
CVN11			-.74		
CVN13			.62		
CVN14			.71		
PVE6				.88	
PVE7				.63	
PVE9				.87	
PVE10				.84	
PVE12				.63	
PVE13				.71	
PVE15				.79	
CVE3					-.74
CVE6					-.74
CVE7					-.70
CVE8					-.62
CVE10					-.67
CVE12					-.72
CVE13					-.64
CVE15					-.73

Note: See Appendix 4 for item label references. One factor excluded because no items met the statistical selection criteria

The 53 items were then fit into a five-factor CFA model. The initial TLI/NNFI and CFI model fit statistics were not adequate scores, the RMSEA statistic was adequate,

and the SRMR statistic was acceptable (see Little, 2013 for criteria), χ^2 (1,315, N = 197) = 3,293.82, p < .001, TLI/NNFI = .77, CFI = .78, RMSEA = .09 (90%: .08-.09), SRMR = .07. Modification indices associated with the fit of this first model revealed several crossloadings between items that were worsening model fit. Crossloading items were removed individually in an iterative process, targeting items whose removal would most improve model fit and targeting specific types of crossloadings (e.g. between items with other factors, between items on different factors, and between items on the same factor), until model fit reached acceptable levels and the five different factors were comprised of equal numbers of indicators.

The first category of items targeted for removal utilizing crossloadings were those items that were a part of one latent construct and had a crossloading stronger than .10 on another latent construct. Three items with this type of problematic crossloading were removed and the deletions improved model fit such that the RMSEA statistic reached an acceptable level, χ^2 (1,117, N = 197) = 2,510.06, p < .001, TLI/NNFI = .82, CFI = .83, RMSEA = .08 (90%: .08-.08), SRMR = .06.

The next set of items targeted for removal using the crossloadings were those items that repeatedly (>1) crossloaded stronger than .10 onto items that were indicators of other factors. After removing 16 items that fit within this category model fit reached acceptable levels across all fit statistics, χ^2 (550, N = 197) = 985.72, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .06 (90%: .06-.07), SRMR = .06. At this point there were 35 items in total in the scale associated with 5 factors. The communicative violence evaluations factor and the communicative violence self-efficacy factor each were comprised of six items, the communicative violence social norms factor and the physical

violence evaluations factor each were made up of seven items, and the physical violence social norms factor consisted of nine items.

In order to reduce the factors to equal numbers of items, five more items were removed from the scale that crossloaded at a level stronger than .10 with other items in the same factor. The removal of these items further improved the model fit statistics, χ^2 (395, N = 197) = 693.53, p < .001, TLI/NNFI = .91, CFI = .92, RMSEA = .06 (90%: .05-.07), SRMR = .06. The final version of the scale with item factor loadings can be found in Table 3. Up to this point all the analysis presented has been conducted on the pre-test sample collected from Amazon mTurk. Next, I present data from the main sample that confirms this factor structure.

Confirming Factor Structure

A CFA model of the selected political violence items was fit to the main survey data, a convenience sample derived from college-aged students, in order to confirm the model found in the pre-test data. Initial model fit was acceptable on several metrics of fit including the CFI and SRMR statistics, was adequate on the RMSEA statistic, though the TLI/NNFI statistic indicated inadequate model fit with the main survey data, χ^2 (395, N = 270) = 993.343, p < .001, TLI/NNFI = .88, CFI = .90, RMSEA = .08 (90%: .07-.08), SRMR = .07. Examining model fit indices suggested that two pairs of items that each described the same behaviors needed to covary, indicating that these pairs of items shared some variance that was unaccounted for by the latent constructs. Allowing both items 2 and 6 in the communicative violence evaluations factor--which both reference showing your middle finger--and items 3 and 6 in the communicative violence perceived norms factor--which both reference swearing--to covary in the model improved model fit to

acceptable levels across all fit statistics, χ^2 (393, N = 197) = 896.56, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .07 (90%: .06-.07), SRMR = .07. The loadings of each indicator of the associated latent construct in this model is also presented in Table 8 and the selected items within each factor are presented in Table 9. The Item # references Table 8 refer to the specific items in each factor indicated by the Item # references in Table 9.

Table 9

Five-Factor Political Violence Scale

	Item #1	Item #2	Item #3	Item #4	Item #5	Item #6
Communicative Evaluations Factor	.72 (.12)/.75 (.08)	.71 (.12)/.86 (.08)	.59 (.10)/.65 (.07)	.75 (.11)/.87 (.09)	.66 (.11)/.71 (.07)	.76 (.10)/.82 (.08)
Communicative Social Norms Factor	.82 (.09)/.61 (.10)	.61 (.10)/ .68 (.09)	-.80 (.10)/-.53 (.11)	.76 (.09)/.64 (.10)	-.77 (.09)/-.43 (.11)	.81 (.08)/.77 (.08)
Communicative Self-Efficacy Factor	.67 (.08)/.62 (.08)	.81 (.09)/.76 (.08)	-.86 (.08)/-.59 (.08)	.88 (.08)/.82 (.06)	.87 (.08)/.82 (.07)	-.85 (.08)/-.52 (.08)
Physical Evaluations Factor	.87 (.05)/.99 (.05)	.78 (.08)/.93 (.05)	.85 (.07)/.88 (.06)	.72 (.08)/.82 (.06)	.73 (.08)/.86 (.05)	.76 (.08)/.93 (.05)
Physical Social Norms Factor	.89 (.04)/.67 (.07)	.64 (.06)/.77 (.08)	-.71 (.05)/-.29 (.12)	.89 (.06)/.84 (.07)	.88 (.04)/.86 (.06)	.62 (.07)/.86 (.06)

Note: Pretest Data Loading (Standard Error)/Main Survey Data Loading (Standard Error). Item # refers to the specific items in each factor outlined in Table 9.

Table 10

Items in each Political Violence Factor

	Item #1	Item #2	Item #3	Item #4	Item #5	Item #6
Communicative Evaluations Factor	It is inappropriate to show your middle finger to make your point in political discussions. (RC)	It is inappropriate to show your middle finger to politicians. (RC)	It is inappropriate to threaten politicians. (RC)	It is inappropriate to swear at [Democrats/ Republicans]. (RC)	It is inappropriate to be uncivil toward federal government employees. (RC)	It is inappropriate to show your middle finger to federal government employees. (RC)
Communicative Social Norms Factor	Most people think it is bad to swear when arguing about politics. (RC)	Most people think it is bad to be uncivil towards politicians. (RC)	Most people think it is okay to swear at politicians.	Most people think it is bad to swear at [Democrats/ Republicans]. (RC)	Most people think it is okay to show your middle finger to [Democrats/ Republicans].	Most people think it is bad to swear at federal government employees. (RC)
Communicative Self-Efficacy Factor	Incivility helps me make my point when arguing about politics.	Swearing helps me make my point when arguing about politics.	Showing my middle finger does not help me make my point when arguing about politics. (RC)	Showing my middle finger helps me make my point when arguing with [Democrats/ Republicans].	Swearing helps me make my point when dealing with federal government employees.	Showing my middle finger does not help me make my point when dealing with federal government employees. (RC)
Physical Evaluations Factor	It is inappropriate to punch politicians. (RC)	It is inappropriate to shove politicians. (RC)	It is inappropriate to punch [Democrats/ Republicans]. (RC)	It is inappropriate to throw rocks at [Democrats/ Republicans]. (RC)	It is inappropriate to spit on federal government workers. (RC)	It is inappropriate to shove federal government workers. (RC)
Physical Social Norms Factor	Most people think it is okay to spit on people when arguing about politics.	Most people think it is okay to throw rocks at politicians.	Most people think it is bad to spit on [Democrats/ Republicans]. (RC)	Most people think it is okay to shove [Democrats/ Republicans].	Most people think it is okay to throw rocks at [Democrats/ Republicans].	Most people think that it is okay to punch federal government employees.

Note: Item # refers to the Item # in each factor in Table 8; Items marked with (RC) are scored such that high scores on the political violence construct are at the bottom of the scale, implying that the item needs to be reverse coded when calculating an observed variable of the political violence construct.

Patterns of Relationships among Factors

A random selection of half the items in the full political violence scale were written with a reverse response pattern, where low scores on the item indicated a high score on the political violence construct. Through the item selection process an uneven amount of reversed and non-reversed items were selected within the factors, meaning that some factors were scored such that positive responses towards violence were associated with high scores and in others positive response towards violence were associated with low scores. Specifically, the factors measuring evaluations and perceived norms associated with communicative violence and measuring evaluations of physical violence are scored such that answers at the bottom of the scale indicate high scores on the political violence construct. Factors measuring perceived norms associated with physical violence and self-efficacy associated with communicative violence are scored such that answers at the top of the scale indicate high scores on the political violence construct. All of the individual indicators in the factors scored such that low scores implied positivity towards political violence were recoded such that high scores on each of the factors in the political violence scale imply positive attitudes towards political violence for use in SEM modeling where the configuration of reverse coding among items is arbitrary for estimation of the relationships (Little, 2013) and the factors are recoded only to aid in interpretation. When reporting the observed means of the political violence variable, each item was coded such that high scores were associated with high levels of the political violence construct. Items that are coded such that low scores imply positive attitudes towards political violence are marked with RC in Table 9.

Each of the factors comprising the political violence scale are highly related as demonstrated in Table 10, which contains the full standardized covariance matrix showing the relationships between the different factors in both the pre-test and main survey datasets. The weakest estimated covariance between factors was observed between the physical evaluations factor and communicative social norms factor (Pretest: $\sigma = .24$, $p < .01$; Main Survey: $\sigma = .22$, $p < .01$). The relationships between the communicative self-efficacy and communicative evaluations factors (Pretest: $\sigma = .56$, $p < .001$; Main Survey: $\sigma = .56$, $p < .01$) and between the physical social norms and physical evaluations factors (Pretest: $\sigma = .56$, $p < .001$; Main Survey: $\sigma = .53$, $p < .01$) were tied for the strongest relationships between factors.

Table 11

Covariance Matrix of Political Violence Factors

	1	2	3	4
1. Comm. Evaluations	-			
2. Comm. Social Norms	.41***/.50***	-		
3. Comm. Self-Efficacy	.56***/.56***	.47***/.29**	-	
4. Physical Evaluations	.46***/.37***	.24**/.22**	.52***/.37***	-
5. Physical Social Norms	.32***/.25**	.51***/.30***	.36***/.25**	.56***/.53***

Note: Pre-test Data/Main Survey Data; Significance of each covariance estimate is in the corresponding space above the diagonal; * $p < .05$, ** $p < .01$, *** $p < .001$

A second order CFA model was fit to the data to create communicative and physical violence latent constructs based on my definition of the political violence construct, which contained both communicative and physical violence elements. Communicative violence evaluations, perceived social norms, and perceived self-efficacy

factors were combined into a single communicative violence latent construct while physical violence evaluations and perceived social norms factors comprised a separate physical violence latent construct. In order for the physical violence latent construct to be locally identified, the variance of the physical violence latent construct was constrained to 1. Initial model fit of the second-order model in the pre-test data was acceptable, χ^2 (395, N = 197) = 724.11, p < .001, TLI/NNFI = .91, CFI = .91, RMSEA = .06 (90%: .06-.07), SRMR = .07, though the second-order model fit slightly worse to the pre-test data than the first-order model. However, modification indices revealed problematic covariances between factors that addressed the same attitude about different intensities of violence. Allowing the communicative social norms and physical social norms factors to covary improved model fit to the same level as the first-order model, χ^2 (395, N = 197) = 697.51, p < .001, TLI/NNFI = .91, CFI = .92, RMSEA = .06 (90%: .05-.07), SRMR = .06. Initial model fit for the second-order model in the main survey data set generated very similar fit statistics as the original model, with only slight worsening of fit on the χ^2 and SRMR indicators, χ^2 (393, N = 197) = 926.02, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .07 (90%: .06-.07), SRMR = .08. No additional covariances were specified in the main survey data model given the only slight differences in model fit between the primary and second-order models. See Table 11 for the factor loadings of each individual political violence latent construct on the second order political violence model.

Table 12

Factor Loadings of Second Order Political Violence Model

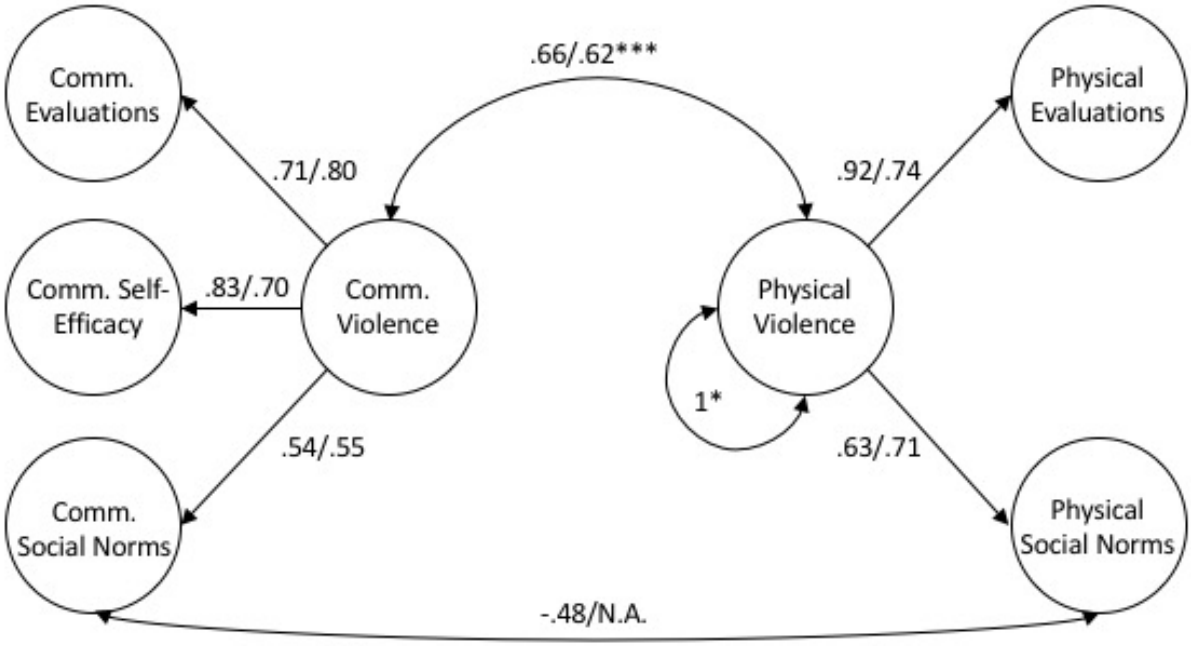
	Communicative Violence	Physical Violence
Communicative Evaluations	.71 (.18)/.80 (.17)	
Communicative Social Norms	.54 (.11)/.55 (.11)	
Communicative Self-Efficacy	.83 (.31)/.70 (.22)	
Physical Evaluations		.92 (1.18)/.74 (.22)
Physical Social Norms		.63 (.14)/.71 (.20)

Note: Pre-Test Data/Main Survey Data

Both communicative and physical political violence are strongly related, indicated by their significant standardized covariance (Pretest: $\sigma = .66$, $p < .001$; Main Survey: $\sigma = .62$, $p < .001$). However, the two latent constructs do not perfectly covary, indicating that the communicative and physical violence factors are measuring distinct though related constructs. A CFA structural model showing the relationships observed in the second order political violence model in the pre-test and main survey data is shown in Figure 2. Based on all of this evidence, the political violence model is substantively similar across the pre-test and convenience samples, with a few minor differences is covariances between indicators that assess the same behaviors and primary-order latent constructs that assess the same attitudes about the different types of political violence.

Figure 2

Second Order Political Violence CFA Model



Note: Pre-test data/Main survey data; * $p < .05$, ** $p < .01$, *** $p < .001$; No covariance estimate was calculated for path between Comm. and Physical Social Norms in the main survey data.

Construct Validity

The second order model of political violence is utilized to calculate the patterns of relationships between communicative violence, physical violence, and the other variables measured in the data set. These covariance relationships test the nomological network that I outlined in chapter three, and provide evidence for the construct validity of the measure. The relationships in the nomological network are tested using both the pre-test and the main survey data iteratively. The measurement model of the pre-test data was calculated without parceling any indicators and produced acceptable levels of model fit across all indicators, χ^2 (1,442, N = 196) = 2,087.19, $p < .001$, TLI/NNFI = .90, CFI = .90, RMSEA = .05 (90%: .04-.05), SRMR = .07. However, the model specified in the

pre-test data excluded the items measuring 1) pro-attitudinal media use, 2) using Reddit to discuss the primary elections, and 3) using news websites to discuss the primary elections, because calculating the latent constructs associated with these variables prohibited the model from converging. Further, the acceptance of political violence (APV) variable was not included in the pre-test data collection and therefore that relationship cannot be estimated using the pre-test data.

In the main survey data correlational parceling was used to calculate the latent constructs that included more than four independent indicators. Initial model fit for the nomological network using the main survey data was acceptable on the RMSEA and SRMR statistics, while fit was not acceptable on the TLI/NNFI and CFI statistics, χ^2 (759, N = 270) = 1,446.40, p < .001, TLI/NNFI = .87, CFI = .88, RMSEA = .06 (90%: .05-.06), SRMR = .07. Modification indices showed that the indicators measuring discussion about the primaries on Facebook, Reddit, and news website did not have much unique variance and covaried highly with discussing the primaries on Twitter. Therefore, the self-report measuring discussion of the primaries on Facebook, Reddit, and news websites was excluded, and this moderately improved model fit. Further examination of modification indices revealed three problematic relationships in the data that were harming model fit. The first problematic relationship was between two parcels measuring political violence (one in Physical Violence Evaluations factor and the other in the APV measure). Another problematic relationship was found between two indicators measuring political trust (one measuring if the opposing political party harms Americans while in office and the other measuring if the federal government harms Americans). The final problematic relationship was between two of the political violence behavior factors

(communicative violence self-efficacy factor and the physical violence perceived social norms factor). Each of these relationships was iteratively allowed to freely covary in the model and these changes ultimately produced model fit that was acceptable according to all fit statistics, χ^2 (649, N = 270) = 1,109.91, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .05 (90%: .05-.06), SRMR = .06. Estimates of the standardized covariate relationships are outlined in Table 12.

Table 13

Standardized Covariance Relationships in Nomological Network

Variable	Comm. Violence	Physical Violence
In-group Bias	-.06 / .06	-.16 / -.08
Political Trust		
Specific Political Trust	-.18* / -.23**	.03 / -.19*
Specific Political Trust – Threat Factor	-.20* / -.16*	-.01 / -.11
Diffuse Political Trust	-.16 / -.15	-.02 / -.10
Diffuse Political Trust – Threat Factor	-.35*** / -.11	-.34*** / -.13
Acceptance of Political Violence (APV)	N.A. /.28***	N.A. / .20*
Pro-Attitudinal Media Use	N.A. / -.04	N.A. / .09
Frequency of Political Social Media Use		
Self-Report of Facebook Use	.04 / N.A.	.01 / N.A.
Self-Report of Twitter Use	.12 / .18	.01 / .04
Observed	N.A. / .80	N.A. / .19
Positive Social Media Communication	N.A. / -.70	N.A. / .01
Negative Social Media Communication	N.A. / -.13	N.A. / -.16
Age[a]	-.04 / -.01	-.09 / .13
Sex (0 = Female; 1 = Male)[a]	.12 / .27***	-.02 / .19*

Note: * $p < .05$, ** $p < .01$, *** $p < .001$; Left side of "/" covariance estimated using pre-test data and right side of "/" covariance estimated using main survey data. NA indicates that scale was not included in the specific data collection time point or that the model could not be estimated with the scale included.

Several of the predictions I outlined in the hypothesized nomological network were not supported by the estimated nomological network. I predicted that in-group bias would be positively related to both communicative and physical political violence, but the estimated nomological network at both time points shows non-significant relationships between in-group bias and political violence. Similarly, I predicted a

positive relationship between political violence and the communication behaviors, including pro-attitudinal media use and political social media use, but the estimated nomological network does not support this prediction.

However, several relationships outlined in the nomological network were supported by the estimated covariance network. Both the communicative and physical factors of political violence are positively and significantly associated with APV, an existing measure of political violence. Several different measures of political trust, including specific political trust, the threat factor of specific political trust, and the threat factor of diffuse political trust, at varying time points were negatively and significantly associated with both political violence factors, indicating that distrust is associated with more positive attitudes towards political violence. All together these results provide mixed support for the construct validity of the political violence measure.

Testing the Theoretic Model

The parts of the theoretic model outlined in chapter two by *Hypotheses 1-5* and *Research Questions 1-3* were tested using the main survey data and SEM based analysis. First a CFA model was fit to test whether the estimates of relationships in the model were meaningful. The indicators of latent constructs were calculated using correlational parceling. Initial base model fit with all the latent constructs was not a positive definite model, indicating that any estimates of parameters in the model may be unreliable. Model fit indices reveled several problematic latent constructs, which were very highly correlated including the different intensities of non-violent political engagement (confrontational and non-confrontational political engagement) and the use of Facebook, Twitter, Reddit, and news websites to discuss the primary elections. The high levels of

colinearity between these variables imply that the latent constructs are measuring the same construct among most participants and therefore the relationships between the highly collinear variables and other variables in the data set are likely the same. Therefore, the latent constructs associated with confrontational political engagement and using Facebook, Reddit, and news websites to discuss the primary elections were removed from the model to resolve the issues with colinearity. Model fit on this slightly reduced model was acceptable on all model fit statistics, χ^2 (652, N = 270) = 1,092.63, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .05 (90%: .05-.06), SRMR = .06. Each of the trust scales used in the model cover different parts of the political trust content domain, and therefore each of the scales is used as an indicator for a second order political trust latent construct. Inclusion of the trust second order construct did not significantly impact model fit, only slightly worsening fit on the SRMR indicator, χ^2 (672, N = 270) = 1,153.12, p < .001, TLI/NNFI = .90, CFI = .91, RMSEA = .05 (90%: .05-.06), SRMR = .07. This model was used to test the structural relationships hypothesized in chapter two.

The first set of hypotheses (1 and 2) predicted that in-group bias and political trust would interact to predict the different political behaviors explored in this project, including communicative and physical political violence and non-violent political engagement. See Table 13 for an overview of the estimated coefficients associated with these behaviors in the model. In order for an interaction effect to be significant on a given variable, both the components that interact together need to be significantly associated with the variable. The data in this model do not support these interaction hypotheses, because only one of the components of the interaction was significantly associated with

each outcome behavior. However, the relationships evident in the observed data provide partial support for my theoretic model of political behavior as described below.

Table 14

Standardized Coefficients and Significance Tests associated with Political Behaviors

	Estimate (Std. Error)	$\Delta\chi^2$	95% C.I.
Comm. Political Violence			
In-Group Bias	.00 (.07)	.00	-.15 – .19
Political Trust	-.24 (.09)	9.30**	-.48 – -.04^
Age	-.11 (.06)	2.47	-.20 – .02
Sex (0 = Female)	.32 (.16)	23.15***	.42 – 1.11^
Political Party Affiliation	-.25 (.05)	12.26***	-.26 – -.04^
Phys. Political Violence			
In-Group Bias	-.14 (.08)	2.24	-.31 – .09
Political Trust	-.24 (.10)	6.67**	-.53 – .02
Age	.12 (.07)	2.14	-.02 – .22
Sex	.19 (.17)	6.24*	.07 – .76^
Political Party Affiliation	.03 (.05)	.10	-.08 – .11
Non-Violent Pol. Behavior			
In-Group Bias	.37 (.08)	20.10***	.14 – .50^
Political Trust	-.12 (.08)	2.34	-.31 – .07
Age	.02 (.06)	.07	-.09 – .14
Sex	-.12 (.14)	3.82	-.01 – .58
Political Party Affiliation	-.10 (.04)	2.39	-.17 – .03

Note: * $p < .05$, ** $p < .01$, *** $p < .001$; ^ 95% C.I. excludes 0

The data show that responses to both the communicative political violence (r^2 = .202) and physical political violence (r^2 = .115) scales were significantly and negatively

associated with political trust, implying that distrust was related to high responses on the political violence scale. However, in-group bias was not significantly related to either communicative or physical political violence factors. Additionally, gender was associated with both intensities of political violence, such that men tended to score higher on the political violence scale than women. Strength of political party identification was significantly associated with communicative political violence, such that stronger identification as a Democrat was associated with high responses on the communicative political violence scale. Age was not significantly associated with either communicative or physical political violence factors.

While political distrust was significantly associated with high responses on the political violence scale and in-group bias was not, the opposite set of relationships were observed between non-violent political engagement and these attitudes. Responses to the scale measuring non-violent political engagement ($r^2 = .186$) was significantly and positively associated with in-group bias, such that greater levels of bias were associated with higher response on the non-violent political engagement scale. Neither political trust nor the other control variables (age, sex, and strength of political party identification) were significantly related to non-violent political engagement. These data imply that rather than interacting to impact political behavior, in-group bias and political trust may operate separately to influence non-violent political behavior and violent political behavior respectively.

The next set of hypotheses (3 and 4) predicted that pro-attitudinal media use is positively associated with in-group bias and negatively associated with political trust, while hypothesis (5) predicted that political social media use would be positively

associated with in-group bias. The data supported the hypotheses about pro-attitudinal media use, but did not support the hypothesis involving political social media. See Table 14 for the standardized coefficients associated with the variables in the model. In-group bias (r^2 = .308) was positively and significantly associated with pro-attitudinal media use, such that more pro-attitudinal media consumption was associated with higher levels of bias, while social media use was not significantly associated with in-group bias. Political trust (r^2 = .119) was negatively and significantly associated with pro-attitudinal media use, such that more pro-attitudinal media use was associated with distrust. While it was not specifically hypothesized, I did test if social media use was associated with political trust, and the two variables were not significantly related.

Table 15

Standardized Coefficients and Significance Tests associated with Attitudes

	Estimate (Std. Error)	$\Delta\chi^2$	95% C.I.
In-Group Bias			
Pro-Attitudinal Media Use	.56 (.15)	31.72***	.28 – 1.34^
Social Media Use (Twitter)	-.01 (.11)	.01	-.42 – .25
Political Trust			
Pro-Attitudinal Media Use	-.25 (.11)	6.68**	-.59 – -.03^
Social Media Use (Twitter)	-.15 (.11)	2.22	-.38 – .13

Note: * $p < .05$, ** $p < .01$, *** $p < .001$; ^ 95% C.I. excludes 0

The first set of research questions (1 and 2) asked if there was an indirect effect between pro-attitudinal media use and measures of the political behaviors through either in-group bias or political trust. These data show some evidence of significant indirect relationships between these variables. See Table 15 for the coefficients associated with the indirect relationships. Pro-attitudinal media use was significantly and positively

associated with the measure of non-violent political engagement through in-group bias, such that greater pro-attitudinal media use was associated with higher levels of bias, which was then associated with higher levels of non-violent political engagement. Pro-attitudinal media use was also indirectly and positively associated with high responses towards the communicative political violence factor, such that more pro-attitudinal media use was associated with lower levels of political trust which was in turn associated with higher levels of communicative political violence. The indirect effect between pro-attitudinal media use and the other political behavior variables, including physical political violence, through both in-group and political trust were tested, but were not estimated to be significantly different from zero.

Table 16

Standardized Coefficients and Significance Tests associated with Indirect Effects

Indirect Path	Estimate (Std. Error)	95% C.I.
Pro-Attitudinal Media Use -> In-group Bias		
Communicative Political Violence	.00 (.06)	-.13 - .13
Physical Political Violence	-.01(.08)	-.24 - .07
Non-Violent Political Engagement	.23 (.13)	.05 - .51^
Pro-Attitudinal Media Use -> Political Trust		
Communicative Political Violence	.07 (.04)	.00 - .16^
Physical Political Violence	.04 (.04)	-.03 - .13
Non-Violent Political Engagement	.02 (.03)	-.02 - .08

Note: ^ 95% C.I. excludes 0

The model using the self-report data supports some of the theoretic model proposed in chapter two and sheds light on the relationships between in-group bias, political trust, political behaviors, and political communication behaviors. The data show

that in-group bias is positively related to non-violent political engagement, while low levels of political trust are associated with both communicative and physical political violence. Pro-attitudinal media use is associated with higher levels of in-group bias and low levels of political trust and has an indirect relationship with non-violent political engagement and communicative political violence through in-group bias and political trust respectively. Next, I review the results of the quantitative text analyses used to calculate the observed social media variables and regression analyses focusing on the relationship between the observed social media variables, political trust, and in-group bias.

Quantitative Text Analysis

In this section I review the results of the quantitative text analysis conducted to create observed measures of social data. I utilize these measures in regressions to test *Hypothesis 6, 7* and *Research Questions 4-8*. However, before I present these results I describe how political social media content was selected for analysis and validity tests associated with these measures.

Overall, 49.63% of participants (n = 134) provided consent to download content from their social media profiles. A total of 82,069 pieces of social media content were collected from these accounts. A total of 26,535 unique words were used in the text of these social media posts. The first step of my analysis was selecting the political content from this population of social data. Initially, my plan was to find political words in this list of all the words in order to filter political content for further analysis. Unfortunately, very few individual words from the social media posts could be identified as related to politics based on the words alone. The list of political words and the total frequency of

posts that contain those words is shown in Table 16. In total, 395 posts included the political words identified in the dataset. This implies that either participants did not talk about politics on social media or that when participants did talk about politics they used few words that I was able to recognize as associated with politics.

Table 17

Political terms in social content data

Term	Post Frequency (%)
Vote	123 (.15)
Trump	40 (.05)
Obama	30 (.04)
Election	20 (.02)
Rubio	18 (.02)
Clinton	16 (.02)
Cruz	16 (.02)
Sanders	13 (.02)
Government	11 (.01)
Kasich	10 (.01)
Political	10 (.01)
Primary	8 (.01)
Voters	8 (.01)
Republican	8 (.01)
Democrat	8 (.01)
Politics	7 (.01)
Conservative	5 (.01)
BlackLivesMatter	3 (.00)
Govt	2 (.00)
ThanksObama	1 (.00)
SaferthanaTrumpRally	1 (.00)
AbsenteeVoter	1 (.00)

As a result of the limitations of my initial approach to identifying political content in the social media posts, I turned to the full dataset of posts and calculated the correlation between each word in the data set and the self-reports of discussion about the primaries on the Facebook, Twitter, Reddit, and news website platforms to identify content that is posted by participants who talked more about politics within the sample

and which is therefore more likely to be regarding politics than other content. Each word that was correlated with a self-report of talking about politics greater than or equal to .10, was used as a "go list" to select content into analysis. This "go list" of terms is compiled in Appendix 5. The correlations produced a metric of the association between each individual word and the posts of participants who say they talk about politics online, and I leveraged this association to target content that is more likely to be political than other pieces of content in the dataset. This process resulted in total of 27,305 total posts (328.97 posts per participant) posted by 31.11% of participants (n = 84) that were more likely to be about politics than the other pieces of social media content. Below I present the frequency of posts, subjects, and sentiment from these 27,305 posts that are more likely to be about politics, and I refer to these data as the selected content.

The frequency of the selected social media data was not evenly distributed across the participants, in part because of platform differences wherein each social media platform allowed access to different amounts of historic content. The distribution of posts across participants is also different in part because some people in the sample had older accounts on these platforms and thus have had more time to post. All participants possessed accounts on the platform at the time that data was collected, but some participant accounts are older than others because of individual participant differences (e.g. some may have felt the need to get an account before others and older participants may have had an account for longer than younger participants). Therefore, I standardized each of the variables by time in order to control for differences the amount of content each participant posted based on differences in platforms and the time that each participant held an account. Specifically, the standardization produced an average

occurrence of a subject or sentiment for each participant that excluded the days that the participant did not post. The frequency of each content analysis variable (the use of a subject or sentiment) was calculated on each day the individual participant posted and the sum of the frequencies was divided by the amount of days on which the participant posted. Functionally, this means that if a person posted on only one day with only one use of positive sentiment, then their score for positive sentiment is 1.00, and that if another person posted on 100 days with 50 uses of positive sentiment, then their score for positive sentiment is .50. When used as a variable, the standardization process produces an indicator of the relative use of each content analysis feature within each participant's posted content. On average participants posted 1.88 pieces of selected content per day that they posted.

The Lexicoder Sentiment Dictionary (LSD), which utilizes a dictionary of sentiment scores associated with words by human coders to estimate the sentiment associated with the text of political news (Young & Soroka, 2012b), was used to code the sentiment of the selected content. The LSD coding dictionary indicated that there were 8,914 posts in the selected data set that included a negative word. In aggregate each participant posted 107.40 posts that included negative words at a rate of .61 negative posts per day the participant posted. In the data there were many more positive words than negative words; in total there were 14,879 posts that included positive words, and in aggregate, each participant posted 179.27 posts that included positive words at a rate of .98 positive posts per day that they posted.

I predicted several correlations between the self-report and observed social media data in chapter three to test the validity of the quantitative text analysis methods. The

correlations assessing these relationships are outlined in Table 17. Only two of these correlations between observed social data and the self-report data were significant, the relationship between both negative and positive sentiment to diffuse political trust was significant and positive, such that higher levels of political trust were associated with greater use of both positive and negative sentiment. I predicted a negative association between negative sentiment and political trust and positive associated between positive sentiment and political trust. The failure of all other correlations to be significantly different from zero and the observed relationship between negative sentiment and political trust occurring in the opposite direction than predicted indicates that the observational measures of political social media use calculated using this data are likely not valid measures of political social media use among this sample. Alternatively, the results contradicting the original predictions could imply that the original predictions were flawed.

Table 18

Validity tests of observed social media variables

Variable	Social Media Metric	Correlation
In-group Bias	Post Rate	-.20
Facebook Political Social Media Use	Post Rate	.14
Twitter Political Social Media Use	Post Rate	.14
Reddit Political Social Media Use	Post Rate	-.08
Specific Political Trust	Negative Sentiment Rate	-.03
Specific Political Trust – Threat	Negative Sentiment Rate	-.09
Diffuse Political Trust	Negative Sentiment Rate	.24*
Diffuse Political Trust - Threat	Negative Sentiment Rate	-.00
Specific Political Trust	Positive Sentiment Rate	-.07
Specific Political Trust – Threat	Positive Sentiment Rate	-.17
Diffuse Political Trust	Positive Sentiment Rate	.21*
Diffuse Political Trust - Threat	Positive Sentiment Rate	-.04

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

In order to test the hypotheses and research questions I performed a number of topic extraction analysis guided by both supervised and unsupervised subject selection methods to find the subjects used in the selected data. I then utilize these subjects in regression analyses with other variables to formally test *Hypotheses 5-7* and *Research Questions 3, 5* and *6*. Unfortunately, given low number of participants that posted selected content, SEM analyses could not be used to estimate the indirect effects between observed social media variables and the measures of political behaviors asked about in

Research Questions 4, 7, and *8.* Therefore, these questions go unaddressed by this analysis.

The unsupervised subject selection method selects the most prominent topics for use in modeling. The topics that were used most in the data set and their frequency of use is reviewed in Table 18. None of the most prominent subjects were comprised of keywords that were clearly political in their context. Two of the subjects (#1 and #8) indicated a participant shared an opinion or a feeling. Several of the other subjects (#3, #6, #7, #9, and #10) reference life in a college town, such as attending events (like the big game) and meeting people. Still other subjects (#2, #4, and #5) share information about the participants' lives such as a photo, a memory, or a statement about religion. The relationship between each of these subjects and the in-group bias and political trust variables is analyzed using different types of regression models.

Table 19

Most prominently used subjects in selected data

#	Description	Keywords	Posts (%)	*M*/Day (*SD*)
1	Sharing Opinion	Gotta, Love, Burn	4,336 (15.88)	.28 (.33)
2	Sharing Photo	Day, Picture	2,213 (8.10)	.13 (.12)
3	Big Event	Lamb, Phi, Halloween, Tree, Columbia, Class, St., Dad, Spring, Big	1,982 (7.26)	.11 (.10)
4	Religious Statement	Bless, God, Life	1,740 (6.37)	.11 (.09)
5	Sharing Memory	Miss, Crazy, Trip	1,701 (6.23)	.10 (.11)
6	Describing Event	Time, Enjoy	1,673 (6.13)	.10 (.08)
7	Meeting People	People, Meet, Amazing, Funny	1,672 (6.13)	.11 (.14)
8	Disclosing Feelings	Feel, Good, Bad	1,525 (5.59)	.09 (.07)
9	Describing Night	Night, Fun, Eat	1,499 (5.49)	.09 (.10)
10	The Big Game	Game, Win	1,397 (5.12)	.09 (.10)

Note: Posts indicates the number of posts that include at least one keyword. The *M*/Day and SD column contains aggregate calculations across all participants that posted selected content.

The relationship between in-group bias and the most prominent subjects in the social data was modeled using a Poisson generalized linear model to test the relationships outlined in *Hypothesis 5* and *Research Question 3* using the most prominent subjects in the data. The fitted model adjusted the deviance by a significant value compared to the null model (ΔDeviance (14) = 624.4, $p < .001$) indicating that the model is a good fit to the data. The coefficients associated with each predictor in the model are outlined in Table 19. The model revealed that many of the predictors were significantly associated with in-group bias. Specifically, the predictor describing the rate at which participants

shared memories in online talk was the only variable not significantly associated with in-group bias. Each of the standardized coefficients (**β**) in this model show the percent change on in-group bias as participant scores on the variables changed. For example, the coefficient associated with pro-attitudinal media use indicates that for each increase in the report of media use by 1, participant reports of in-group bias were .42% higher. The observed relationship between pro-attitudinal media use and in-group bias further supports the relationship found in the SEM estimation of my theoretic model (*Hypothesis 3*). Also, the significant relationship between in-group bias and the overall social media post rate supports *Hypothesis 5*, which suggested that the frequency of political social media posts would be positively related to in-group bias. However, given the lack of political content observed in the collected social media and the lack of validity associated with the observed social media variables, I can only conclude that the relationships observed between in-group bias and the observed social media variables are likely spurious.

Table 20

Relationships between most prominent social content and in-group bias

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	.21 (.01)	.0042	14.67***
Post Frequency	.18 (.04)	.0055	3.95***
Negative Sentiment	-.70 (.11)	-.0075	-6.11***
Positive Sentiment	-.31 (.12)	-.0042	-2.77**
Sharing Opinion	.45 (.20)	.0022	2.34*
Sharing Photo	1.17 (.25)	.0027	4.67***
Big Event	-1.52 (.25)	-.0031	-6.01***
Religious Statement	-.95 (.32)	-.0015	-3.01**
Sharing Memory	-.10 (.22)	-.0002	-.47
Describing Event	2.01 (.35)	.0027	5.67***
Meeting People	1.32 (.33)	.0021	3.96***
Disclosing Feelings	.72 (.23)	.0019	3.17***
Describing Night	-.81 (.31)	-.0011	-2.62**
The Big Game	-2.15 (.24)	-.0039	-8.82***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Linear regression models were used in order to test *Hypotheses 6* and *7* and *Research Questions 5* and *6*, which addressed the relationship between political trust and the observed social variables, using the most prominent subjects selected in an unsupervised fashion. Many of the models examining the relationship between the most prominent observed social variables and the self-report political trust variables were not a

significant fit to the data. For example, the model predicting specific political trust using the most prominent observed social content was not a significant fit to the data, F (14, 69) = .99, p = .47. Also, the model predicting the threat factor of specific political trust using the most prominent observed social content was not a significant fit to the data, F (14, 69) = 1.61, p = .10. Further, the model predicting the threat factor of diffuse political trust using the most prominent observed social content was not a significant fit to the data, F (14, 69) = 1.02, p = .45. This lack of model fit implies that the estimates of relationships calculated in these models is unreliable.

However, the model estimating the relationships between the most prominent social content and diffuse political trust was a significant fit to the data, F (14, 69) = 1.91, $p < .05$ ($r^2 = .28$). The coefficients associated with each of the predictors in this model is outlined in Table 20. Only one of the observed social content variables was associated with diffuse political trust, specifically making religious statements was significantly and negatively associated with diffuse political trust. This result implies that if a person made posted about religion then they were more likely to report lower levels of diffuse political trust. However, given the lack of political talk in the collected social data and the lack of validity with the observed social data, this result could be spurious. Therefore, *Hypotheses 5* and *6*, which predict relationships between positive and negative sentiment and political trust, were not supported by this data.

Table 21

Relationships between most prominent social content and diffuse political trust.

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	-.07 (.03)	-.21	-1.96
Post Frequency	-.04 (.11)	-.22	-.46
Negative Sentiment	.24 (.19)	.38	-1.27
Positive Sentiment	.10 (.24)	.23	.43
Sharing Opinion	.35 (.29)	.32	1.19
Sharing Photo	.79 (.56)	.26	1.40
Big Event	.04 (.54)	.01	.07
Religious Statement	-1.57 (.68)	-.40	-2.30*
Sharing Memory	-.13 (.52)	-.04	-.24
Describing Event	-.22 (.63)	-.05	-.35
Meeting People	.62 (.64)	.18	.96
Disclosing Feelings	-.70 (.44)	-.28	-1.61
Describing Night	-1.11 (.70)	-.22	-1.58
The Big Game	-.89 (.50)	-.26	-1.80

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The supervised subject selection method found the subjects that were that were most strongly associated with both in-group bias and the political trust self-report variables, and then formally tested the independent impact of the subjects and the other observed social variables on in-group bias and political trust using regression to provide another test of *Hypotheses 5-7* and *Research Questions 3, 5* and *6*.

In order to test *Hypothesis 5* and *Research Question 3* regarding the relationship between in-group bias and the observed social data the subjects most strongly related to in-group bias were selected. The subjects that exhibit the strongest positive correlational relationship with in-group bias are outlined in Table 21. Even though these are the strongest relationships in the data set, none of these subjects is significantly correlated with in-group bias. Only one of the subjects exhibiting the strongest correlations with in-group bias was clearly political (#4) and that subject was about a current political communication course that several participants were enrolled in and recruited from. The other topics were largely related to events that often occur in life (and the life of college-aged students), such as disclosing feelings (#1), expressing an evaluation of something (#2, #8), events in their life specifically moving (#3), discussing events that the participant is anticipating or looking forward to (#6), discussing close relationships (#7, #10), and providing instructions (#5). Interestingly one of the subjects correlated with in-group bias was concerning lifestyle personality Emily Post. I test the relationship between these subjects and in-group bias using regression.

Table 22

Highest correlations between subjects and in-group bias

#	Subject	Keywords	Correlation	Posts (%)	*M*/Day(*SD*)
1	Disclosing Feelings	Hair, run, wrong, hope	.14	787 (2.88)	.05 (.05)
2	Evaluation (a)	Would, deserve	.14	774 (2.83)	.05 (.07)
3	Moving	Room, move, freshman	.14	295 (1.09)	.02 (.02)
4	Pol. Com. Course	MU, ProfHayley, Interest	.13	427 (1.56)	.00 (.01)
5	Instructions	Bring	.13	81 (.30)	.00 (.01)
6	Anticipating Event	Wait, celebrate, home	.11	1,208 (4.42)	.07 (.07)
7	Close Relationship (a)	Friend, family	.11	1,155 (4.08)	.07 (.07)
8	Evaluation (b)	Perfect	.11	328 (1.20)	.02 (.03)
9	Emily Post	Emily, Post	.11	461 (1.69)	.05 (.12)
10	Close Relationship (b)	Hand, hold, stand	.10	335 (1.23)	.02 (.03)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The model predicting in-group bias with the highest subject correlations was estimated using a Poisson generalized linear model. The fitted model adjusted the deviance by a significant value compared to the null model (ΔDeviance (14) = 807.6, $p <$ .001) indicating that the model is a good fit to the data. The coefficients associated with each predictor in the model are outlined in Table 22. The model revealed that many of the predictors were significantly associated with in-group bias; only the predictor describing the rate at which participants posted social content not significantly associated with in-group bias. Each of the standardized coefficients (**β**) in this model show the percent change on in-group bias as participant scores on the variables changed. For example, the

coefficient associated with pro-attitudinal media use in this model indicates that for each increase in the report of media use by 1, participant reports of in-group bias were .35% higher. The observed relationship between pro-attitudinal media use and in-group bias further supports the relationship found in the SEM estimation of my theoretic model (*Hypothesis 3*). Including the other subjects that are associated with in-group bias causes the relationship between post frequency and in-group bias to disappear from this result, implying that *Hypothesis 5* was not supported by this model. However, given the lack of political content in the collected social data and the lack of validity associated with the self-report variables, I can only conclude that many of the other significant relationships observed in this model are spurious.

Table 23

Relationships between correlated social content and in-group bias

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	.17 (.02)	.0035	11.13***
Post Frequency	-.04 (.04)	-.0014	-1.00
Negative Sentiment	-.50 (.09)	-.0053	-5.67***
Positive Sentiment	-.55 (.09)	-.0073	-5.81***
Disclosing Feelings	4.52 (.58)	.0033	7.70***
Evaluation (a)	2.65 (.55)	.0025	4.78***
Moving	4.79 (.89)	.0018	5.39***
Pol. Com. Course	9.50 (1.71)	.0017	5.56***
Instructions	10.16 (2.82)	.0013	3.60***
Anticipating Event	1.22 (.32)	.0018	3.89***
Close Relationship (a)	-.94 (.44)	-.0014	-2.13*
Evaluation (b)	4.25 (.89)	.0022	4.79***
Emily Post	1.56 (.12)	.0044	13.41***
Close Relationship (b)	4.78 (1.08)	.0016	4.42***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

To test *Hypotheses 6* and *7* and *Research Questions 5* and *6* using subjects selected in the supervised method, I found the subjects that exhibited the lowest correlations with each of the self-report political trust variablesand then tested the relationships using regression. Most of the subjects with the strongest negative relationships with specific political trust, outlined in Table 23, were non-political.

However, one subject focused on the shooting of Michael Brown in Ferguson, MO that occurred in August 2014, which was likely political in nature given the political context of the Ferguson events. The remaining subjects were about normal events in college-aged people's lives such as describing things they have done (#2), close relationships (#3, #5), disclosing emotions (#4, #7), evaluating something (#6, #8, #9), and discussing work (#10). I test the relationship between each of these social content variables and specific political trust using regression.

Table 24

Lowest correlations between subjects and specific trust

#	Subject	Keywords	Correlation	Posts (%)	*M*/Day(*SD*)
1	Michael Brown	Michael Brown, black, kill	-.35***	162 (.59)	.01 (.02)
2	Describing Activity	Listen, music, sleep, stay, till, jess	-.30**	692 (2.53)	.04 (.05)
3	Close Relationship (a)	Hand, hold, stand	-.25*	335 (1.23)	.02 (.03)
4	Disclosing Emotion (a)	Afraid, show, color	-.23*	441 (1.62)	.03 (.03)
5	Close Relationship (b)	Father, front	-.21*	176 (.64)	.01 (.02)
6	Evaluation (a)	Perfect	-.21*	328 (1.20)	.02 (.03)
7	Disclosing Emotion (b)	Smile, tear, face	-.20*	444 (1.62)	.03 (.04)
8	Evaluation (b)	Would, deserve	.20*	774 (2.83)	.05 (.07)
9	Evaluation (c)	Weird, memory, status, wall, color, favorite	-.20*	1,091 (4.00)	.07 (.08)
10	Work	Hard, work	-.19	784 (2.87)	.04 (.05)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The model predicting specific political trust with the social content that was the lowest correlation with specific political trust was a significant fit to the data, F (14, 69) = 2.25, $p < .05$, ($r^2 = .31$). The coefficients associated with each of this model are outlined in Table 24. However, despite the significant model fit, only the pro-attitudinal media use and a social content variable concerning an evaluation (that something is perfect) were significantly related to trust in the regression model. Both of these variables were related to specific political trust, such that as more pro-attitudinal media was consumed and

evaluations were offered participants were more distrustful. The observed relationship with pro-attitudinal media use and specific political trust supports the relationship observed using the SEM estimation procedures. The relationship in the results between specific political trust with the observed social content is likely spurious given the lack of political content in the collected social media and the lack of validity of the observed social data variables.

Table 25

Relationships between correlated social content and specific political trust

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	-.29 (.10)	-.31	-2.89**
Post Frequency	.05 (.22)	.08	.24
Negative Sentiment	-.54 (.50)	-.31	-1.09
Positive Sentiment	.59 (.45)	0.47	1.33
Michael Brown	-13.79 (8.20)	-.22	-1.68
Describing Activity	-1.06 (3.73)	-.05	-.28
Close Relationship (a)	-3.42 (6.67)	-.10	-.51
Disclosing Emotion (a)	-5.26 (4.11)	-.18	-1.28
Close Relationship (b)	-5.02 (6.27)	-.11	-.80
Evaluation (a)	-9.49 (4.53)	-.27	-2.09*
Disclosing Emotion (b)	-.31 (4.27)	-.12	-.07
Evaluation (b)	-.49 (2.51)	-.03	-.19
Evaluation (c)	1.34 (2.46)	.10	.55
Work	-1.12 (2.79)	-.05	-.40

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The threat factor of the specific trust variable was significantly related to all of the subjects in the social content outlined in Table 25. The strongest correlation was again between the trust variable and mentioning Michael Brown. Other subjects that were significantly related to trust were evaluations of something (#2, #7), describing activities (#3), disclosing emotions (#4, #5, #10), discussing failure (#6), and close relationships

(#8, #9). I test the relationship between these subjects and the threat factor of specific political trust using regression.

Table 26

Lowest correlations between subjects and threat factor of specific political trust

#	Subject	Keywords	Correlation	Posts (%)	*M*/Day(*SD*)
1	Michael Brown	Michael Brown, black, kill	-.42***	162 (.59)	.01 (.02)
2	Evaluation (a)	Guess, pretty, cool	-.36***	881 (3.23)	.05 (.06)
3	Describing Activities	Listen, music, sleep, stay, till, jess	-.36***	692 (2.53)	.04 (.05)
4	Disclosing Emotion (a)	Smile, tear, face	-.36***	444 (1.62)	.03 (.04)
5	Disclosing Emotion (b)	Kinda, sad, practice, worth	-.35***	617 (2.26)	.04 (.05)
6	Discussing Failure	Mistake, make, matter	-.33**	814 (2.98)	.05 (.06)
7	Evaluation (b)	Joke, laugh, dream, funny, color	-.33**	523 (1.92)	.03 (.05)
8	Close Relationship (a)	Hand, hold, stand	-.32**	335 (1.23)	.02 (.03)
9	Close Relationship (b)	Woman, mother, man, kind	-.31**	675 (2.47)	.04 (.04)
10	Disclosing Emotion (c)	Plan, mind, free, open, heart	-.30**	1,020 (3.74)	.07 (.08)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The regression model predicting the threat factor of specific trust using the social content was a significant fit to the data, F (14, 69) = 2.72, $p < .01$ ($r^2 = .36$), and the

coefficients associated with this model are outlined in Table 26. The only significant predictor of trust in the regression model was discussing Michael Brown, such that more discussion of Brown was associated with greater distrust. While, the social data may not be particularly valid there may actually be a relationship between discussing the shooting of an unarmed African American by police online and political trust. Future research should investigate this relationship further.

Table 27

Relationships between correlated social content and threat factor of specific political trust

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	-.20 (.10)	-.20	-1.92
Post Frequency	-.23 (.22)	-.36	-1.06
Negative Sentiment	.57 (.49)	.31	1.18
Positive Sentiment	.39 (.42)	.30	.94
Michael Brown	-18.16 (8.00)	-.28	-2.27*
Evaluation (a)	-.62 (2.90)	-.04	-.21
Describing Activities	-.96 (3.69)	0.04	.26
Disclosing Emotion (a)	-7.39 (4.13)	-.29	-1.79
Disclosing Emotion (b)	-5.15 (4.11)	-.23	-1.25
Discussing Failure	2.12 (4.48)	.11	.47
Evaluation (b)	-4.94 (4.04)	-.22	-1.22
Close Relationship (a)	1.63 (6.92)	.05	.24
Close Relationship (b)	-3.19 (3.14)	-.13	-1.02
Disclosing Emotion (c)	1.81 (2.35)	.15	.77

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The lowest correlations between diffuse political trust and subjects found in the social data are presented in Table 27, and even though these were the strongest negative correlations in the dataset there are no significant correlations observed between any subject and diffuse political trust. These subjects focused on disclosing feelings (#1, #6,

#10), on disclosing thoughts (#2), on describing activities (#3, #4, #8, #9), and promoting evaluations (#5, #7). The relationship between each of these subjects and diffuse political trust is tested using regressions.

Table 28

Lowest correlations between subjects and diffuse political trust

#	Subject	Keywords	Correlation	Posts (%)	*M*/Day(*SD*)
1	Disclosing Feelings (a)	Head, state, wanna, end	-.17	899 (3.29)	.06 (.06)
2	Disclosing Thoughts	Idea, realize	-.17	218 (.80)	.01 (.02)
3	Describing Activities (a)	Homework, wear, cuz, sleep, taylor	-.16	863 (3.16)	.06 (.08)
4	Describing Activities (b)	Sing, son, drive, drink	-.15	235 (.86)	.02 (.02)
5	Evaluation (a)	Awkward, moment	-.14	256 (.94)	.01 (.02)
6	Disclosing Feelings (b)	Reason, remember, matter, tough	-.14	512 (1.88)	.03 (.03)
7	Evaluation (b)	Guess, pretty, cool	-.12	881 (3.23)	.05 (.06)
8	Describing Activities (c)	Final, week	-.12	786 (2.88)	.04 (.05)
9	Describing Activities (d)	Comment, hit, ready, cheer, live	-.11	904 (3.31)	.06 (.09)
10	Disclosing Feelings (c)	Feel, Good, Bad	-.09	1,525 (5.59)	.09 (.07)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The regression model predicting diffuse political trust using the observed social content was a significant fit to the data, F (14, 69) = 2.30, $p < .05$ ($r^2 = .32$). The coefficients associated with this model are outlined in Table 28. However, none of the extracted estimations of social content were significantly associated with political trust.

Positive sentiment was significantly associated with diffuse political trust such that greater use of positivity was associated with greater trust, which may provide support for *Hypothesis 7*. However, given the lack of validity associated with the indicators of social content it is likely that this relationship is spurious.

Table 29

Relationships between correlated social content and diffuse political trust

Variable	Estimate (Std. Error)	β	t-value
Pro-Attitudinal Media Use	-.07 (.03)	-.19	-1.84
Post Frequency	-.08 (.08)	-.35	-.98
Negative Sentiment	.17 (.17)	.26	.98
Positive Sentiment	.32 (.14)	.70	2.33*
Disclosing Feelings (a)	-1.34 (.82)	-.22	-1.63
Disclosing Thoughts	-1.85 (2.69)	-.09	-.68
Describing Activities (a)	-.70 (.56)	-.16	-1.23
Describing Activities (b)	-1.07 (2.13)	-.06	-.50
Evaluation (a)	-1.21 (2.26)	-.06	-.53
Disclosing Feelings (b)	-2.06 (1.69)	-.19	-1.22
Evaluation (b)	-.83 (.95)	-.15	-.87
Describing Activities (c)	-.58 (.97)	-.08	-.59
Describing Activities (d)	.16 (.61)	.04	.27
Disclosing Feelings (c)	.32 (.74)	.06	.43

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The lowest correlations between the threat factor of diffuse political trust and subjects found in the social data are presented in Table 29, and all the correlations between the observed subjects and political trust were significant. One of these subjects again referenced the shooting of Michael Brown and the incidents in Ferguson, MO (#4). Other subjects focused on describing activities (#1, #9), on disclosing thoughts (#2), on offering encouragement (#4, #7), describing a close relationship (#5, #6), and disclosing feelings (#10). Interestingly there was also one subject that referenced cancer and people fighting the disease (#8), which may have been describing reasons why someone should participate in an event such as a fundraiser for cancer research. I test the relationship between these subjects and the threat factor with regression, but the model was not a significant fit to the data, F (14, 69) = 1.64, p = .09, indicating that any estimates are unreliable.

Table 30

Lowest correlations between subjects and threat factor of diffuse political trust

#	Subject	Keywords	Correlation	Posts (%)	*M*/Day(*SD*)
1	Describing Activities (a)	Listen, music, sleep, stay, till, jess	-.31**	692 (2.53)	.04 (.05)
2	Disclosing Thoughts	Idea, realize	-.29**	218 (.80)	.01 (.02)
3	Michael Brown	Michael Brown, black, kill	-.28**	162 (.59)	.01 (.02)
4	Encouragement (a)	Strong, stay	-.28**	210 (.77)	.01 (.02)
5	Close Relationship (a)	Woman, mother, man, kind	-.25*	675 (2.47)	.04 (.04)
6	Close Relationship (b)	Hand, hold, stand	-.23*	335 (1.23)	.02 (.03)
7	Encouragement (b)	Special, stop, cry, lol	-.23*	962 (3.49)	.06 (.06)
8	Cancer	Cancer, honor, fight, die	-.21*	362 (1.33)	.01 (.02)
9	Describing Activities (b)	Summer	-.21*	300 (1.10)	.02 (.02)
10	Disclosing Feelings	I'm, bored	-.20*	1,249 (4.58)	.07 (.11)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

The results of these regression analyses provide further support for *Hypothesis 3*, regarding the positive relationship between in-group bias and pro-attitudinal media use. However, given the lack of validity of the observed social media variables and the low amount of political content in the collected social data, the results provide little support for *Hypotheses 5-7* and *Research Questions 3, 5* and *6*. Further, given the low number of participants who posted the selected social data, the relationships in the data were estimated using regression rather than SEM. Therefore, the indirect effects asked about in *Research Questions 4, 7,* and *8* could not be tested with this data because of the small sample size.

Conclusion

To begin this chapter, I outlined the results associated with the design and validation of my measure of political violence. I polled experts in the field who largely agreed that the proposed political violence scale adequately covered the content domain of the political violence construct. Some qualitative feedback was offered by the experts, which I incorporated into the scale. The scale was distributed to a pre-test sample and the results from this sample were used to reduce the scale to five factors made of six items that are a part of a second-order model of communicative and physical political violence. I then collected data from an independent student sample that confirmed the factor structure of the scale. The construct validity of the political violence scale was tested and some, though not all, of the predicted relationships were found in my data. Overall, the political violence scale was found to cover the entire content domain of political violence and there is some evidence supporting the validity of the scale.

I then used the political violence scale to test my theoretic model. I proposed that in-group bias and political trust interacted to be related to both non-violent and violent political engagement. The data showed that political violence was significantly associated with political trust (such that distrust was associated with more positive responses on the violence scale) and was not associated with in-group bias. Conversely, non-violent political engagement was associated with in-group bias (such that more bias was associated with greater engagement), but was not associated with political trust. Further, my data showed that pro-attitudinal media consumption was associated with higher levels of in-group bias and lower levels of political trust (or otherwise stated: higher levels of political distrust). Pro-attitudinal media use also had a positive indirect effect on non-

violent political engagement and communicative political violence through in-group bias and political trust respectively.

In this project I collected a large amount of social data that was authored by the participants. Unfortunately, I could not reliably detect enough political content to enable quantitative text analysis procedures on the data that produced valid variables of political social media use. Therefore, the analysis is conducted on data that is more likely to be political, which was found by finding the words that correlated with self-reports of talking about politics. I also calculated the frequency that participants posted and the sentiment used in these posts. The validity associated with these observed measures of self-report data was tested using correlations, but largely the results do not support the validity of the quantitative text analysis metrics. I tested the relationship between the observed subjects used in the social data and the in-group bias and trust variables, but most of the relationships found are likely spurious. However, there was one relationship found between discussion of the death of Michael Brown and the surrounding incidents that may have been associated with distrust. Further, many of the regression models further provide support for the relationship between pro-attitudinal media use and the attitudes, in-group bias and political trust, which was previously outlined by the structural equation model.

Chapter 5: Discussion

In this project I have explored the theoretical links between in-group bias, political trust, communication behaviors, including pro-attitudinal media consumption and political social media use, and political behaviors, including non-violent and violent political engagement. In order to test the theoretic model outlining these relationships, I designed and validated a scale measuring political violence. Further, I utilized a novel data collection plan and analysis procedure in an attempt to develop observational measures of social media communication. I elaborate on the theoretic and methodological contributions of this project and situate these findings within the broader literature below.

Theoretic Contributions

In chapter two, I outlined a theoretic model explaining the relationship between in-group bias, political trust, communication behaviors, including pro-attitudinal media consumption and political social media use, and political behaviors, including non-violent and violent political engagement. The data I have collected suggest some important modifications to my theoretic model. Further, the evidence presented in this project helps identify future research in this area to test the causal nature of the processes that undergird the relationships between communication, attitudes, and political behavior.

Modeling Political Behavior

Political violence is a form of political behavior, much like non-violent political behaviors such as voting, volunteering, and donating to campaigns. Therefore, the decision to commit political violence is governed by the same sort of processes that describe how political decisions are made more generally. Many political decisions are made using attitudes that operate as information processing shortcuts (Popkin, 1994;

Sniderman et al., 1991). These information processing shortcuts allow an individual to bypass the estimation of gains and costs associated with a decision to engage in a specific behavior and to assume that engaging in said behavior is the best course of action available. From this overarching perspective, I hypothesized that two attitudes, in-group bias and political trust, which both function as information processing shortcuts associated with political decision making (e.g. Hetherington, 2005; Lodge & Taber, 2013), would interact to influence the decision to engage in both political violence and non-violent political behaviors.

In other words, I hypothesized a dual attitude process to model whether a person would engage in violent or non-violent political behaviors, such that in-group bias was related to the intensity of both violent and non-violent political behavior and political trust was related to whether political engagement took violent or non-violent forms. The dual attitude model of political behavior implicitly assumes that political violence and non-violent political engagement are orthogonal behaviors, such that people who might engage in political violence are unlikely to also engage in non-violent political behaviors. In part, this conceptualization of the relationship between political violence and non-violent political behavior is inspired by Mouffe (2013) who argues that people turn to violence when they believe that non-violent political behaviors are ineffective at accomplishing their specific political goals.

However, the data did not support this dual attitude model but indicated that in-group bias and political trust are independently associated with non-violent political behavior and political violence respectively. Specifically, results from the current project suggest that in-group bias is associated with non-violent political engagement such that as

bias increases a person is more likely to engage in politics non-violently. Trust was associated with political violence such that participants who were more distrustful were more likely to respond positively towards both communicative and physical political violence. In other words, political violence and non-violent political engagement are motivated by two independent single attitude processes.

The single attitude processes found in the results further suggest that political violence and non-violent political behavior may not be orthogonal political behaviors, but rather that violent and non-violent political behaviors may be utilized together in various ways to accomplish political goals. Anecdotally, the complementary nature of violent and non-violent politics can be observed within the current political climate. Donald Trump has hosted many rallies, largely attended by people who plan to support him using non-violent political behaviors such as voting, volunteering, or donating to his campaign. The emergence of political violence at these rallies by people who are also engaging in non-violent political behaviors supports the notion that violent and non-violent political behaviors may be used complementarily within specific contexts to accomplish political goals. Future research should explore the specific motivations behind political violence and whether these motivations are similar to or different from the goals motivating non-violent political behaviors.

The results presented regarding the relationship between in-group bias and non-violent political engagement support the previous research literature. Mutz (2002, 2006) found that political ambivalence, which is in part a function of low in-group bias, is related to non-participation in non-violent political behaviors such as voting. The results presented in the current study elaborate on the relationship between in-group bias and

non-violent political behaviors at the opposite end of the spectrum, showing that high in-group bias is related to greater levels of non-violent political engagement.

Further, my findings support previous research linking political trust with political violence. Miller (1974), Burke (1984), and Mouffe (2013) all argue that low political trust, or distrust that is accompanied by perceptions of threat, are associated with political violence. The results of this study showed that low levels of political trust were associated with positive responses towards both communicative and physical political violence.

The relationships revealed in the current data between in-group bias, political trust, and the political behaviors, including both violent and non-violent political engagement, support the larger model of political behavior, which posits that attitude-based information processing shortcuts involving political trust and in-group bias are utilized by people to make political decisions (e.g. Hetherington, 2005; Lodge & Taber, 2013). Future research should explore the causal nature underlying the relationships between in-group bias, political trust, and political behaviors, including non-violent and violent political engagement in order to understand whether in-group bias and political trust directly cause non-violent political engagement and political violence. Specifically, experiments should be designed that utilize a specific treatment, such as exposure to pro-attitudinal media (e.g. Cappella & Jamieson, 1996; Garrett et al., 2014; Levendusky, 2013; Mutz & Reeves, 2005), to illicit changes in-group bias and political trust in order to test if changes in the in-group bias and political trust attitudes cause changes in responses to the scales measuring the political behaviors compared to a control treatment. Longitudinal designs can also be utilized to measure if naturalistic changes to in-group

bias and political trust correspond to changes in responses to the scales measuring non-violent and violent political behaviors. This future research exploring the causal relationships between in-group bias, political trust, and the political behaviors, including both violent and non-violent political engagement should focus on determining the nature of the information processing shortcuts that utilize in-group bias and political trust to impact whether political engagement takes violent or non-violent forms.

However, the results presented in the current project also clash with some findings from previous research. Sageman (2011), Gupta (2001), and Burke (1941) argue that in-group bias is related to political violence. The data in the current project show that there is little relationship between preferring a political in-group and violent political behavior. Using the dual attitude theoretic model, I also hypothesized that high political trust would be associated with non-violent political behavior, because trust would lead people to perceive that non-violent participation in the existing political system could be an effective way to accomplish political goals. However, the collected data do not support this proposition since political trust was not associated with non-violent political engagement.

One component of my hypothesized model, the relationships between the attitudes, in-group bias and political trust, and the intensity of violent and non-violent political behavior, was not formally tested using the current data. I predicted that confrontational non-violent political behavior was more intense than non-confrontational non-violent political behavior, while physical political violence was more intense than communicative political violence. My hypothesized model argued that higher intensity behaviors would be associated with higher scores on the in-group bias and political trust

variables than the less intense behaviors. Therefore, intensity could be tested by examining the means of the in-group bias and political trust that are associated with the different score levels on the different intensities of political behavior (i.e. comparing the means of in-group bias and political trust of high and low physical political violence group and a high and low communicative political violence group). However, the specific hypotheses that I outlined in chapter two focused on testing the associations between variables in the model and are therefore inadequate to test the intensity concept. Future research should examine whether in-group bias and political trust are related to the intensity of political behaviors by testing whether the mean levels of the in-group bias and political trust attitudes among those that report differing intensities of non-violent and violent political behavior.

Pro-Attitudinal Media Use

Previous research has shown a reciprocal and causal effect between pro-attitudinal media use and in-group bias (Feldman et al., 2014; Garrett et al., 2014; Levendusky, 2013; Slater, 2007). However, the causal relationship between pro-attitudinal media use and in-group bias is contingent on whether a person normally consumes pro-attitudinal media, such that normal use minimizes effects on in-group bias (Arceneaux & Johnson, 2013). The current data confirmed a strong relationship between pro-attitudinal media use and in-group bias, such that higher consumption of pro-attitudinal media was associated high levels of bias.

Previous research has also revealed a complex relationship between news consumption and political trust. Some research suggests that more news consumption is associated with greater trust, because political trust leads people to consume media and

that surveillance of political groups through media promotes knowledge about the actions of political groups, which fosters even more political trust (Norris, 2000). Other research has found no difference in the amount of media consumed by those who trust the government and those who distrust the government and that the effect of news consumption on trust may be contingent on existing levels of trust, such that those who are trusting may become even more trusting and those that distrust the government are unaffected by the news media (Avery, 2009). However, exposure to negative content in different types of political media, including strategic and conflict oriented frames in news and negative campaign communications, may promote political distrust (Cappella & Jamieson, 1996; Mutz & Reeves, 2005). Given the presence of negativity and extreme partisan voices on partisan media (e.g. Levendusky, 2013), I predicted that pro-attitudinal media use would be related to lower levels of political trust. My data confirmed this hypothesis, showing that greater pro-attitudinal media use was associated with lower levels of political trust.

Further, my data revealed an indirect effect between pro-attitudinal media use and non-violent political engagement and communicative political violence through in-group bias and political trust respectively. Indirect effects in the context of cross-sectional data imply that variance in one variable is related to the variance in an outcome variable through a third variable that mediates the relationship. The findings from my model show that pro-attitudinal media use was associated with higher levels of non-violent political behavior, because the pro-attitudinal media use was associated with higher levels of in-group bias. Pro-attitudinal media use was also associated with higher levels of

communicative political violence, because higher levels of pro-attitudinal media use were associated with lower levels of political trust.

However, the data revealed that pro-attitudinal media use was not indirectly related to physical political violence through political trust, potentially because of the estimated relationship between political trust and physical political violence. When testing the relationship between political trust and physical political violence using the χ^2 metric, the relationship was significant. However, when testing the relationship between political trust and physical political violence using the 95% confidence interval surrounding the estimate, the confidence interval crossed zero which implies the estimated effect is not significant.

There are several reasons why the relationship between political trust and physical political violence was not significant utilizing the 95% confidence interval metric. Physical political violence is a more intense form of political violence than communicative violence, and therefore the decision to commit physical political violence may only be influenced by very low levels of political trust. The student sample from which my main survey was collected may not have had enough variance on the lower end of the political trust scale to accurately estimate the relationship between physical political violence and political trust. This possibility suggests that non-significant relationship observed between trust and physical political violence may be a variation in the sample. Alternatively, physical political violence could be caused by different exogenous variables such as trait aggressiveness (e.g. C. A. Anderson & Bushman, 2002) and authoritarianism (e.g. Hetherington & Weiler, 2009), which previous research has also found to be associated with violence. Future research should investigate these

possibilities by further exploring the relationships between other variables and physical political violence and employing samples that exhibit variance on the low end of the political trust measures.

The relationships and indirect effects observed in the current study do not show causal relationships between the pro-attitudinal media use, attitude, and political behavior variables because the data is cross-sectional. However, the relationships and indirect effects described here do suggest that future research investigating the causal relationships between these variables may be fruitful. Future research should utilize experimental and longitudinal designs to investigate the causal relationship between these variables. Given the contingent effects of pro-attitudinal media use on in-group bias, future experimental research that manipulates pro-attitudinal media consumption in an effort to impact in-group bias and political trust should measure and control for regular pro-attitudinal media consumption or employ designs that allow participants to select media in a ecologically valid manner (see Arceneaux & Johnson, 2013; Garrett et al., 2014; Garrett & Stroud, 2014 for examples of ecologically valid research designs)

Also, self-report measures of pro-attitudinal media use are inaccurate measures of absolute media use (Prior, 2009a, 2009b). Therefore, future research should employ observational measures of pro-attitudinal media use to calculate more exact estimations of the relationships between pro-attitudinal media use and the other variables. It is important to note however, that the inaccuracy associated with self-report measures of pro-attitudinal media use do not undercut the relationships observed in my data, because self-reports of pro-attitudinal media use do provide an accurate representation of the relative media use among the sample, meaning that those who consume more pro-

attitudinal media likely report higher levels of consumption than those who consume less pro-attitudinal media. Therefore, the relationships observed in pro-attitudinal media use and the other variables in my data should hold in future research employing observational measures of pro-attitudinal media use.

Political Social Media Use

My hypothesized model predicted that the frequency of political social media use would be related to in-group bias and that the sentiment utilized in political social media communications would be related to political trust. In the hypothesized model, in-group bias was associated with more frequent and intense political behaviors. Given that talking about politics online is a political behavior, I predicted that in-group bias would make political social media communication more frequent. Previous research has shown that low political trust is a function of exposure to negative and conflict oriented political communication (Cappella & Jamieson, 1996; Mutz & Reeves, 2005). Therefore, in the hypothesized model I predicted that authoring negative political social media communication would be associated with lower levels of trust and, conversely, that positive political social media communication would be associated with higher levels of political trust.

However, the current data did not support any of the propositions that I made regarding the relationships between political social media communication and political trust or in-group bias. The self-report variable utilized to measure the relative frequency of political social media use in the sample, specifically a measure of talking about the primaries on Twitter, was not significantly associated with in-group bias or political trust. The observed variables measuring the frequency and sentiment of political social media

communication were not valid indicators of political social media use, largely because much of the sample did not frequently talk about politics on the platforms from which data was collected. Therefore, while there were some relationships found in the data between the observed social media variables and political trust and in-group bias, it is very likely that these relationships are spurious.

However, the lack of relationships in this data could imply several different things. First, the lack of relationships between social media use and in-group bias and political trust could be a function of the sample. It could be the case that the sample did not talk about politics online, and the observational data shows that this may have been the case. Therefore, among a different sample that actually engages in political social media use, the predicted relationships might be observed. The lack of political social media use in the current sample may also indicate that overall population of people that talk about politics online is small and so any observed effects of that behavior may not be widespread. Alternatively, the current sample may have talked about politics online, but not use the specific platforms that were asked about in the self-report and from which the observational data was collected. This would imply that including other platforms where people discuss politics or ensuring that the sample talked about politics on the platforms being examined during the recruitment process would help gather data illustrating the relationship between social media use and political attitudes. Beyond these sample issues, future research should explore and refine both the self-report and observed measures of political social media use using psychometric methods.

Methodological Contributions

Beyond the theoretical contributions of this project, I make several methodological contributions to the field. First, I designed, validated, and utilized a new self-report measure of political violence, which includes both communicative and physical political violence factors. I also utilized a novel data collection plan to collect political social media posts authored by participants and to analyze and aggregate the data using quantitative text analyses. I outline the strengths and weaknesses of each of these contributions below.

Measure Design

I designed and validated a self-report measure of political violence that is oriented towards a broad definition of political violence (e.g. Potter, 1999) including both communicative and physical violence factors. First, I authored 96 question items that were systematically sampled from the content domain of the political violence construct and a panel of experts in the field rated the scale and suggested qualitative feedback. The results of the expert ratings of the scale were largely positive, indicating that the items adequately covered the content domain of the political violence construct. Some qualitative feedback was incorporated into the items in the scale.

Next, the 96 items were distributed to a pre-test sample and the resultant data was utilized to identify the best factor structure for the scale and to select the items for the final scale. The factor structure and item selection analyses produced a scale composed of 30 items arranged into five factors of six items each. The factors measured evaluations, perceived social norms, and self-efficacy sub-factors that were associated with communicative political violence and evaluations and perceived social norms associated

sub-factors that were associated with with physical political violence. No items loaded onto a factor measuring self-efficacy associated with physical political violence with enough unique variance to meet the criteria required in the item selection process. This may indicate that items measuring self-efficacy associated with physical political violence are subject to some sort of bias in responses. Social desirability bias may be particularly influential on measures of self-efficacy associated with political violence. The five sub-factors were organized into two second-order model creating the communicative and physical political violence latent constructs.

The final political violence scale was then distributed to a second sample. The data from the second sample confirmed the sub-factor structure and the second-order model of the items measuring political violence that were selected using the pre-test data. Both the pre-test data and the data from the second sample were utilized to test the construct validity of the political violence measure. The tests indicated that some the relationships expected based on my theoretic model were not significant, specifically in-group bias was not significantly related to the measures of political violence. However, some of the trust scales were significantly related to both of the political violence measures. Further, the physical and communicative political violence factors were significantly related to another measure of political violence, the acceptance of political violence, which has been previously utilized in research exploring political violence (e.g. Hawthorne, 2013; Hawthorne & McKinney, 2013; Hawthorne & Warner, 2013). While some of the relationships were not significant, the results provide some support the construct validity of the political violence measure.

The political violence scale is organized into a second-order model, where each of the attitudes about communicative and physical political violence (evaluations, perceived social norms, and self-efficacy) are organized as latent constructs that act as indicators for larger communicative and physical violence latent constructs. However, there are only two attitudinal factors comprising the physical political violence latent construct, since the items assessing self-efficacy associated with physical political violence did not uniquely load onto a separate factor. This two indicator arrangement for the physical political violence latent construct leaves the construct under identified without further model specifications (e.g. constraining the variance of the latent construct). Future research should explore the physical political violence construct and develop a third sub-factor that could be combined with the others to create a locally just-identified physical political violence latent construct when modeling the full second-order political violence latent constructs.

Measure design is an iterative process and future research should continue to develop evidence supporting the validity of the political violence scale. The measure designed here assesses attitudes related to political violence, rather than being an observational measure of political violence. Future research should specifically focus on elaborating the construct validity of the political violence measure designed here by assessing the relationship between the current political violence scale and other measures of violence. One specific type of violence measure that could be easily deployed is the punishment of a hypothetical deviant, or likely more applicable, the punishment of hypothetical opposing partisan deviant. For example, a measure could be deployed that asks participants to act as a juror and to assign a punishment to a hypothetical cross-

partisan politician who has been found guilty of corruption. This type of hypothetical punishment measure has been used to measure violence in research in social psychology testing terror management theory (e.g. Greenberg, Solomon, & Pyszczynski, 1997; Jonas & Greenberg, 2004; Solomon, Greenberg, & Pyszczynski, 1991) and future research should use this type of measure further elaborate on the construct validity of the political violence scale.

As a part of future work, empirical validity should be tested on the political violence scale. Empirical validity is established by showing that movement in an outcome variable that has been experimentally manipulated, corresponds to variance in the measure of the outcome variable (Borsboom et al., 2004). For example, experiments could be conducted that utilize a mortality salience prime in order to show that experimentally manipulated propensities towards violence correspond to differences in measurement of the political violence scale and therefore establishing evidence of empirical validity. Research on terror management theory has shown that a mortality salience prime, such as a participant writing about their own death, is associated with violent responses towards perceived deviants such as criminals (Solomon, Greenberg, & Pyszczynski, 2000). Similar mortality salience primes should produce different levels of responses in the political violence measure compared to those who are unprimed, and such a result would provide evidence of the empirical validity associated with the political violence scale.

Quantitative Text Analysis

As part of my main survey data collection, I collected the posts made by participants to several social media platforms including Facebook, Twitter, Reddit, and

Disqus. In this data, I intended to find content that was related to politics in order to analyze how political content posted to social media was related to in-group bias and political trust. However, my initial attempt to find political content involved searching for political words, but I could not identify many words that were related to politics on their face. As a next step to find political content, I found the words that were most associated with high participant self-reports of discussion about the presidential primaries on social media, in order to find words that were posted by people in my sample who talked more about politics. These words were used to identify social media content that was more likely to be about politics than other pieces of content. I located the emergent topics used within the selected social media content and then used a dictionary based sentiment analysis to assign a positive and negative sentiment score to that content. The frequency of posting, the use of subjects, and the use of sentiment in social media content was linked to each participant's survey data in order to model relationships between the observed measures of social media content and survey data.

Unfortunately, the observed measures of political social media content did not adequately pass tests of the validity of these measures. This implies that any significant relationships found between the observed social media data and the survey data are likely spurious. Ultimately, this effort failed because the student sample mostly did not talk about politics on the social media platforms from which data was collected in this project. Despite this failure, this type of effort to collect social data and to create observed measures of social media content is likely still a useful pursuit and there are several ways that this approach could be modified to be more useful in future research.

There are several potential solutions that might help researchers collect social media content about politics on and associate that content with survey data for future projects. One limitation in the current project was that the sample rarely discussed politics on the platforms from which data was collected. Therefore, in order to ensure that political social media content can be collected, a sample that does talk about politics on a social media platform should be recruited. For example, a sample could be recruited from a social web space, such as a subreddit on the Reddit platform where politics are discussed or a Twitter hashtag stream where people talk about politics. Efforts to recruit people from these social spaces may be difficult, but could be utilized to fruitfully examine the relationship between social media content posted about politics and measured survey data. While a sample recruited because they talk about politics online would not likely be generalizable to an entire national population, the results could be generalized to those who normally talk about politics online.

Social data could also be collected from participants in an experimental situation where participants are instructed to post about a politics. For example, previous research has used instructions to prompt participants to live-tweet a debate in an experimental setting (e.g. Houston, Hawthorne, et al., 2013; Houston, McKinney, et al., 2013; McKinney, Houston, & Hawthorne, 2013). Such experimental situations can nudge participants to engage in political talk and the relationships observed in this data might indicate relationships that are also present among more naturalistic political social media use. However, it is likely that forcing participants to post on social media about politics may produce different effects than occur naturally, specifically effects will likely be observed among those who do not normally communicate about politics on social media

and which are unlikely to occur naturally. Therefore experiments prompting social media use should measure whether participants generally talk about politics on social media in order to more accurately estimate an effect among those who use political social media normally.

More ambitiously, future research could also design an artificial social environment for use in online experiments wherein participants access an online survey that collects self-report data regarding their political attitudes and are then exposed to an artificial social environment where they can engage in simulated social media behaviors about politics. Such experimental environments would have the ability to measure the types of content that participants select to view as well as record data regarding any interactions the participants have with the platform (e.g. liking, posting, sharing). Of course, building an artificial social environment for participants to interact in would sacrifice some ecological validity of the findings. While it is technically possible to import data from participants' existing political social networks to generate a more ecologically valid artificial social environment, such efforts would likely be thwarted by the privacy restrictions associated with many social media platforms. Ideally, all of these approaches should be utilized in future research, as each could help shed light on the connection between the political content produced by people on social media and attitudes measured by self-report survey measures.

The program utilized to conduct the analyses of the social media content from research participants in the current study was *WordStat*, a proprietary software. There are several benefits to using such a proprietary piece of software like *WordStat*, including that there is a graphical user interface, that technical support was available, and there

were many features to increase convenience and analysis speed (i.e. standard preprocessing tools such as a lemmatizer and dictionaries to label parts of speech). However, there were several difficulties that arose from using the software. For example, importing the data into the program for analysis and then exporting the results after analysis in order to link the results of the quantitative text analysis with the survey data was difficult. On a more fundamental level, the algorithms utilized to conduct the subject extraction component of the quantitative text analysis are proprietary and cannot be accessed and examined by researchers. This means that many of the specific details associated with the subject extraction analysis algorithms are unknown, much like the specific details associated with the maximum likelihood estimator that is a part of the SPSS or Stata statistical packages are unknown. However, there are open source software alternatives available to conduct quantitative text analysis, specifically, the Python programming language with the open source code library, the Natural Language Toolkit (NLTK; see nltk.org). Open source solutions should be utilized in future analyses involving quantitative text analysis (and in other types of analysis) in order for researchers to fully account for the specific details associated with the statistical analysis algorithms that create their results.

Limitations and Future Directions

There are several important limitations to my overall findings in this project. While I collected data at multiple data points, all of the data was cross-sectional in nature implying that the data cannot test the causal nature of these associations or the empirical validity of the political violence measure. Future research should explore the causal relationships between these data points using experimental or longitudinal study designs.

The data collected to test the theoretic model was collected from students while the pre-test data was collected from a sample of Amazon mTurk workers. Both of these samples are limited and non-generalizable to any larger country-based population. Future research should deploy these measures with a more generalizable sample to see if the relationships observed in my data hold more generally to people across the country.

There were also several issues associated with the measurement of key variables in my model. The most pressing measurement shortcoming was associated with the observed political social media communication variables. The sample talked infrequently about politics using the platforms from which data was collected in this project. The lack of political social media content reduced the validity of the observed social media communication variables and limited the inferences that I could make with my data. I have previously reviewed sample recruitment and design options that may help researchers gather political social media content authored by participants in future research.

There were some measurement shortcomings associated with the survey self-report data. Some of the self-report variables that were measuring similar types of behaviors were highly collinear in the data set. For example, social media use regarding the presidential primaries was measured on both Facebook, Twitter, Reddit, and on news websites platforms, but the measures were so collinear that Facebook, Reddit, and news website discussion of the primaries was removed from the model in order to improve model fit. Similarly, the two intensities of non-violent political engagement, confrontational and non-confrontational engagement, were highly collinear and confrontational political engagement had to be dropped from the model in order to

accurately estimate the relationships between the other variables. In both of these cases the best performing variable, based on modification indices, was selected and retained in the model. Future research should try to ameliorate these problems by using different measures social media use on different platforms, which perhaps are not so linear with each other in their construction, and non-violent political engagement while replicating the tests of the relationships in this data.

I have previously underscored the need for future research to focus on testing the causal nature of the relationships observed in the data. However, given the incidences of political violence during the current campaign season (Lind, 2016; Mathis-Lilley, 2016), the 2016 presidential election context provides an excellent opportunity to interview and collect data to address questions regarding the motivations of political violence from people who have directly participated in political violence. This type of micro level dataset could be particularly informative regarding the attitudinal and communicative pre-conditions associated with violent political behavior, while also providing further ways to test the validity of self-report measures of political violence. Therefore, future research could utilize interviews and focus groups focused on understanding the perspectives of people who have participated in political violence to increase our knowledge in this area.

Conclusion

This project has made several theoretic and methodological contributions to how researchers understand political violence and the role of communication behaviors foster political behavior. Perhaps the most significant contribution is the measure of political violence. This measure should be used in future research in order to more fully explore

the relationships between different behaviors, attitudes, and political violence. I also utilized a novel data collection and analysis plan to collect observed variables that allow the content of social media communications to be modeled. While the methodological process collecting and analyzing the social media communication of participants was ultimately flawed because the participants rarely discussed politics on the platforms from which data was collected, several lessons were garnered from the process that will improve future efforts to gather data and develop observed variables measuring political social media communication.

The data gathered in this project reveal several important findings about the links between political behaviors, including non-violent and violent political engagement, and attitudes, including in-group bias and political trust, suggesting that the decision to engage in political behaviors is associated with these attitudes. Higher levels of in-group bias were associated with greater non-violent political engagement while political distrust, and perceptions of threat that accompany a lack of trust, were associated with political violence. The results do not indicate that people either engage in non-violent or violent politics, but that based on the configuration of attitudes people could engage in both, neither, or one of these political behaviors to accomplish their specific goals. Further, these results also indicate that people may utilize information processing shortcuts related to in-group bias and political trust to make decisions to act in politics.

The data also indicated that high levels of pro-attitudinal media use are associated with both high levels of in-group bias and low levels of political trust. Further, the data revealed indirect effects between pro-attitudinal media use and non-violent political engagement through in-group bias, as well as between pro-attitudinal media use and

communicative political violence through political trust. These indirect effects suggest that there may be causal associations between pro-attitudinal media use and both violent and non-violent political behaviors through in-group bias and political trust respectively that should be investigated by future research.

Ultimately, this project is an early effort in a line of research to investigate the relationships between communication behaviors and political violence. I have successfully designed and collected evidence providing some support for the validity of a political violence scale. The early evidence presented in this project suggests several potential possibilities of causal relationships between pro-attitudinal media use, political attitudes, and political behaviors that may ultimately be uncovered by future research.

If the relationships presented in this project hold under causal test designs, the results would show that political trust and pro-attitudinal media consumption are causes of violent political behavior. The fractured media environment that has led to the proliferation of choice among consumers (Prior, 2007), and which allows partisans to select into pro-attitudinal mass media information environments (Garrett, 2009; Garrett & Stroud, 2014), may be decreasing political trust among those partisan media consumers and creating conditions were political violence among this group is more likely. Further, causal tests that support this project would show that pro-attitudinal media use fosters non-violent political engagement among the group who consumes such media by increasing in-group bias. Together, pro-attitudinal media may be creating a group of people who love their political in-group, loathe their political out-group, are distrustful of opposing partisans and the government, and work to accomplish their political goals using both non-violent and violent political tactics.

The presidential candidacy of Donald Trump has been accompanied by outburst of violence at rallies and events (Lind, 2016; Mathis-Lilley, 2016). This study suggests that the violence accompanying the rise of Trump may be caused by low political trust among Trump supporters that has been fostered by pro-attitudinal media consumption. In the United States, political trust in government has reached the lowest point since measurement of political trust began in the late 1950s (Doherty, Kiley, Tyson, & Jameson, 2015). The political consequences of political trust is an understudied area (Hetherington, 2005), and this project contributes to the literature on political trust by suggesting that low trust is associated with political violence. Future research should further elaborate on the role of trust in deciding to commit political violence and on the further tangible outcomes associated with low political trust.

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Appendices

Appendix 1: Self Report Measures

Demographics

What is your age in years?
Drop down list with responses from "18" to "Over 80" incrementally increasing

What is your biological sex?
Female, Male, Prefer not to respond

With which race/ethnicity described below do you most closely identify?
Asian, Black, Hispanic/Latino, Other (Identify with text entry), White

What term below best describes your political partisanship?
(1) Strong Democrat, Democrat, Leaning Democrat, Neither Republican or Democrat, Leaning Republican, Republican, Strong Republican (7)

What term below best describes your political ideology?
(1) Extremely Liberal, Liberal, Leaning Liberal, Neither Liberal or Conservative, Leaning Conservative, Conservative, Extremely Conservative (7)

In the 2016 General Election if you were presented with the ideal Democrat and Republican candidates for whom would you vote?
(1) Democrat, Republican (2)

Specific political trust

The opposing partisan identity from each participant is inserted into the [Democrats/Republicans] slot.

Section adapted from incumbent based trust scale (Craig et al., 1990)
You can trust [Democrats/Republicans] to do what is right.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

It often seems like [Democrats/Republicans] are run by a few big interests looking out for themselves rather than being run for the benefit of all people. (Reverse coded)
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Most elected [Democrats/Republicans] try to serve the public interest, even if it is against their personal interests.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

When [Democrats/Republicans] make statements to the American people on television or in the newspapers, they are usually telling the truth.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Unless we keep a close watch on them, many [Democrats/Republicans] will look out for special interests rather than for all the people.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

[Democrats/Republicans] in public office usually try to keep the promises they have made during the election.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Most elected [Democrats/Republicans] are well-qualified to handle the problems that we are facing in this country.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Quite a few [Democrats/Republicans] are not as honest as the voters have a right to expect (Reverse coded)
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Most [Democrats/Republicans] can be trusted to do what is right without our having to constantly check on them.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Threat factor
Some [Democrats/Republicans] want to hurt the United States.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Some [Democrats/Republicans] in office deliberately try to harm Americans.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Quite a few [Democrats/Republicans] do not truly love the United States.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

[Democrats/Republicans] in office create immoral laws.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

If a [Democrats/Republicans] win in the 2016 general election I fear for the financial wellbeing of my family.

(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Having a [Democrat/Republican] in office hurts my economic prospects.

(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Diffuse political trust (Hetherington, 1998, 2005)

People have different ideas about the government in Washington. These ideas don't refer to Democrats or Republicans in particular, but just to the government in general. We want to see how you feel about these ideas. For example:

How much of the time do you think you can trust the government in Washington to do what is right-just about always, most of the time, or only some of the time?

(1) Just about always, Most of the time, Some of the time (-1)

Do you think that people in government waste a lot of the money we pay in taxes, waste some of it, or don't waste very much of it?

(1) Not very much, Some, A lot (-1)

Would you say the government is pretty much run by a few big interests looking out for themselves or that it is run for the benefit of all the people?

(1) For the benefit of all, Few big interests

Do you think that quite a few of the people running the government are crooked, not very many are, or do you think hardly any of them are crooked?

(1) Hardly any, Not many, Quite a few (-1)

Threat Factor

Do you think that quite a few of the people running the government want to hurt the United States, not many want to hurt the United States, or do you think hardly any of them want to hurt the United States?

(1) Hardly any, Not many, Quite a few (-1)

Do you think that the government is not a threat to your economic wellbeing, is some of a threat to your economic wellbeing, or is a big threat to your economic wellbeing?

(1) Not a threat, Some of a threat, A big threat (-1)

Do you think that the government is run by quite a few people who hate America, is run by not many people who hate America, or is run by hardly any people who hate America?

(1) Hardly any, Not many, Quite a few (-1)

Do you think that the government hardly ever harms Americans, sometimes harms Americans, or often harms Americans?
(1) Hardly ever, Sometimes, Often (-1)

Do you think that hardly any people in the government are immoral, that not many people in the government are immoral, or quite a few people in the government are immoral?
(1) Hardly any, Not many, Quite a few (-1)

In group bias (Iyengar et al., 2012; Skitka et al., 2005)

On a scale ranging from *0*, implying *Very Cold*, to *100*, implying *Very Warm*, how warmly or coolly do you feel towards the following political groups and politicians?
Liberals: Sliding Scale with range 0 to 100
Conservatives: Sliding Scale with range 0 to 100
Democrats: Sliding Scale with range 0 to 100
Republicans: Sliding Scale with range 0 to 100
Hilary Clinton: Sliding Scale with range 0 to 100
Bernie Sanders: Sliding Scale with range 0 to 100
Barack Obama: Sliding Scale with range 0 to 100
Donald Trump: Sliding Scale with range 0 to 100
Ben Carson: Sliding Scale with range 0 to 100
Marco Rubio: Sliding Scale with range 0 to 100

Pro-Attitudinal Media Use

How frequently, on a range from *Zero times* to *Several times a day*, do you think you will use the following partisan media sources is the upcoming week?
Fox News: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
MSNBC: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
CNN: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
The New York Times: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
The Washington Post: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
Liberal leaning blogs or websites: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)
Conservative leaning blogs or websites: (1) Zero Times, Infrequently, A few times, Sometimes, Often, Every day, Several times a day (7)

Non-violent Political Engagement (Mutz, 2002)
Note: * added to the scale to have three indicators to estimate a latent construct

Confrontational Participation
During the recent campaign, did you talk to any people to try to convince them why they should vote for or against a particular candidate? (1) No, Yes (2)

Did you work for any political party or candidate in the recent election campaign? (1) No, Yes (2)

Did you share content online to persuade people to vote for or against a particular candidate?* (1) No, Yes (2)

Non-confrontational Participation
Did you attend any meetings or election rallies for any candidate or political party? (1) No, Yes (2)

Did you put up a political yard sign or bumper sticker or wear a campaign button for any candidate or political party? (1) No, Yes (2)

Did you give any money to a political party or candidate? (1) No, Yes (2)

Appendix 2: Preliminary Items Measuring Political Violence

Content Domain

I seek to measure attitudes that covary with verbal and physical political violence in order to explore how these attitudes are related to other attitudes about politics and politicians and communication behaviors. Ultimately, this scale measuring political violence will be used in online and paper surveys. Ajzen and Fishbein (1980) and Ajzen (1991) show that evaluations of a behavior, the perceived social norms towards a behavior, and the perceived behavioral control (efficacy) are some attitudes that covary with engaging in behaviors. Therefore, I sample from the attitudinal content domain of evaluations, perceived social norms, and efficacy towards political violence. I divide political violence into two factors that are related to verbal and physical political violence.

Verbal political violence focuses on the use of language and other symbols to cause emotional and physical harm to the well being of a target. Verbal political violence encompasses activities like incivility, cursing, harassing, and threatening.

Physical political violence focuses on the use of the body or a weapon to cause emotional or physical harm to the well being of a target. Physical political violence encompasses activities like spitting on, roughing up, shoving, or using a weapon (operationalized as a rock in the questions).

Political violence as a behavior at times takes on a specific target. I build some of these targets and situations into the questions. Specifically, items are phrased to position the target of violent behavior as opposing political groups (written as [Democrats/Republicans] in the questions below and that will use piped text to insert the proper text in the final survey), politicians, or government more generally (e.g. federal government, government workers). However, I also measure attitudes towards political violence behaviors that do not include a specific target.

I systematically sample from the broad content domain specified above. For both the verbal and political violence factors I sample items related to the evaluations of behaviors, the perceived social norms of a behavior, and the perceived efficacy of a behavior. Each of the verbal and physical behaviors outlined above are included within each attitude type. Further, all of the targets of the behaviors and the specific situations outlined above are included as well.

Response options will range from 1 (*Strongly Agree*) to 7 (Strong*ly Disagree*) on each item. Half of the items on the scale are reverse scored and have negative wording. Items will be combined into two factors and latent constructs will be estimated using SEM based analysis. Participants will be instructed to: "Please indicate how much you agree or disagree with the following statements about behaviors in politics."

Content Domain Dimensions of Political Violence Scale

Attitude	Verbal Behavior	Physical Behavior	Target
Evaluation	Incivility	Spitting on	None
Subjective Norm	Cursing	Roughing Up	Politician
Efficacy	Harassing	Shoving	Opposing Partisan
	Threatening	Using a weapon (rock)	Government/Gov. Worker

Items within the Political Violence Content Domain

Attitude	Verbal Political Violence	Physical Political Violence
Evaluation	*No Target* 1. Incivility is good if people use it to stand up for the political views they believe in. 2. True patriots sometimes curse to make their points. 3. Harassment is a bad tool to use in politics. 4. Making threats is a bad political strategy. *Politician Target* 5. Good citizens are uncivil to politicians. 6. Cursing at politicians is a bad behavior. 7. Harassment of politicians is a bad behavior. 8. It is okay to threaten politicians to make your point. *Opposing Partisan Target* 9. It is good to be uncivil towards [Democrats/Republicans]. 10. Cursing at [Democrats/Republicans] is a bad behavior. 11. Harassing [Democrats/Republicans] is a good strategy to make them understand. 12. It is never okay to threaten [Democrats/Republicans] to make you point. *Government Target* 13. Incivility does not help you make you point when you are dealing with the federal government. 14. When dealing with the federal government cursing is a bad behavior. 15. Harassment is a bad strategy to help get your point across when dealing with the federal government. 16. Threats are a good tool when dealing with the federal government.	*No Target* 1. It is okay to spit on people when talking about politics. 2. Some people need a little roughing up in politics. 3. Shoving people to make your point in politics is a bad behavior. 4. Throwing rocks at people is a bad strategy to make your point heard in politics. *Politician Target* 5. True patriots spit on politicians to make their point. 6. It is never okay to rough up politicians to make them change their views. 7. Shoving politicians is a bad strategy in politics. 8. Some politicians deserve a rock through the window. *Opposing Partisan Target* 9. It is bad to spit on [Democrats/Republicans] to make your point. 10. Some [Democrats/Republicans] deserve to get roughed up. 11. Sometimes it is necessary to shove [Democrats/Republicans] to make your point. 12. It is never okay to throw rocks at [Democrats/Republicans]. *Government Target* 13. Spitting on federal government workers never helps you get your point across. 14. Sometimes people from the federal government need to get roughed up. 15. It is bad behavior to shove federal government workers to make a point. 16. Throwing rocks at federal government workers is a good strategy to make your point heard.

Perceived Norms	*No Target* 1. Everybody thinks it is okay to be uncivil when talking about politics. 2. Nobody thinks it is good to curse when talking about politics. 3. Most people have harassed someone because of politics at one point in time. 4. Most people would never threaten someone because of politics. *Politician Target* 5. Most people think it is bad to be uncivil when talking to politicians. 6. Everybody curses at politicians sometimes. 7. Everyone knows it is never okay to harass a politician. 8. Everyone knows that sometimes politicians get threatened. *Opposing Partisan Target* 9. Most people have been uncivil towards [Democrats/Republicans] at one point in time. 10. Everyone thinks that it is bad to curse at [Democrats/Republicans]. 11. Most people think it is okay to harass a [Democrat/Republican]. 12. Most people think that it is bad to threaten [Democrats/Republicans]. *Government Target* 13. Everybody thinks that it is bad to be uncivil when dealing with the federal government. 14. Everyone knows that it is bad to curse when dealing with the federal government. 15. Most people think that is is bad to harass federal government workers. 16. Everyone knows that it is okay to make threats when dealing with the federal government.	*No Target* 1. In a political disagreement, most people think it is okay to spit on people. 2. Everyone knows that is bad to rough someone up because of politics. 3. In a political disagreement, most people think it is okay to shove someone. 4. Everyone knows that sometimes rocks get thrown in politics. *Politician Target* 5. Most people think it is bad to spit on politicians. 6. Everyone knows that sometimes politicians get roughed up. 7. Most people think it is never okay to shove a politician. 8. Most people have thrown a rock at a politician at one point in time. *Opposing Partisan Target* 9. Nobody thinks it is good to spit on [Democrats/Republicans]. 10. Everyone knows that it is bad to rough up [Democrats/Republicans]. 11. Most people think is I good to shove [Democrats/Republicans]. 12. Everyone knows that no [Democrat/Republican] deserves to get rocks thrown at them. *Government Target* 13. Everyone knows that it is bad to spit on federal government workers. 14. Everybody knows that sometimes federal government workers get roughed up. 15. In a disagreement, everyone knows it is bad to shove a federal government worker. 16. Nobody thinks that any federal government workers deserve to get rocks thrown at them.

Efficacy	*No Target* 1. Sometimes I can be uncivil when I talk about politics. 2. I get so upset I curse sometimes when I talk about politics. 3. I never could harass someone over politics. 4. I cannot imagine threatening someone because of politics. *Politician Target* 5. I cannot imagine being uncivil when talking to a politician. 6. I could never curse at a politician. 7. Sometimes I feel like I could harass a politician. 8. I can imagine threatening a politician. *Opposing Partisan Target* 9. I could not be uncivil towards [Democrats/Republicans]. 10. I feel like I could curse out some [Democrats/Republicans]. 11. I can imagine myself harassing some [Democrats/Republicans]. 12. I could never threaten a [Democrat/Republican]. *Government Target* 13. I could see myself being uncivil when dealing with the federal government. 14. I could never curse when dealing with a federal government worker. 15. I cannot imagine harassing a federal government worker. 16. I could see myself threatening a federal government worker.	*No Target* 1. I could see myself spitting on someone because of politics. 2. I could never rough someone up because of politics. 3. Sometimes I imagine myself shoving someone because of politics. 4. I could never imagine myself throwing rocks because of politics. *Politician Target* 5. Sometimes I feel like I could spit on a politician. 6. I cannot imagine roughing up a politician. 7. I could never shove a politician. 8. Sometimes I think about throwing rocks at politicians. *Opposing Partisan Target* 9. I could never spit on a [Democrat/Republican]. 10. Sometimes I think that I could go out and rough up some [Democrats/Republicans]. 11. I feel like could shove some [Democrats/Republicans]. 12. I cannot see myself throwing rocks at [Democrats/Republicans]. *Government Target* 13. I could never spit on a federal government worker. 14. There are some federal government workers that I could imagine roughing up. 15. I could never shove a federal government worker. 16. I could throw some rocks at federal government workers.

Appendix 3: Expert Survey for Content Validity

All items are adapted from that framework outlined by Haynes, et al. (1995).

Items Addressing Overall Scale

Please indicate how much you agree or disagree with the following statements about the entire scale as a whole.

The array of items selected is representative of content domain of the target construct.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

The instructions to participants are appropriate.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

The different targets of political violence described in the scale cover the domain of targets that are relevant to the political violence construct.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

The different violent behaviors described in the scale cover the domain of violent behaviors that are relevant to the political violence construct.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Do you have any comments or feedback regarding the scale that is not captured in the statements above?
Open ended response

Items Addressing Each Factor

Please indicate how much you agree or disagree with the following statements about the factor.

The individual items within the factor are appropriately combined into the factor.
(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Do you have any comments or feedback regarding the factor that is not captured in the statements above?
Open ended response

Items Addressing Each Item

Please indicate how much you agree or disagree with the following statements about the item.

The language used in the item is precise (has only one meaning in the context of question).

(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

The item response form is appropriate for the item.

(1) Strongly Disagree, Disagree, Slightly Disagree, Neither Disagree or Agree, Slightly Agree, Agree, Strongly Agree (7)

Do you have any comments or feedback regarding the item that is not captured in the statments above?

Open ended response

Appendix 4: Final Items Measuring Political Violence

Attitude	Communicative Political Violence (CV)	Physical Political Violence (PV)
Evaluation (E)	*Implicit Target* 1. It is appropriate to be uncivil to make your point in political discussions. 2. It is appropriate swear to make your point in political discussions. 3. It is inappropriate to show your middle finger to make your point in political discussions. 4. It is inappropriate to threaten others to make your point in political discussions. *Politician Target* 5. It is appropriate to be uncivil to politicians. 6. It is inappropriate to swear at politicians. 7. It is inappropriate to show your middle finger to politicians. 8. It is inappropriate to threaten politicians. *Opposing Partisan Target* 9. It is appropriate to be uncivil towards [Democrats/Republicans]. 10. It is inappropriate to swear at [Democrats/Republicans]. 11. It is appropriate to show your middle finger to [Democrats/Republicans]. 12. It is inappropriate to threaten [Democrats/Republicans]. *Government Target* 13. It is inappropriate to be uncivil towards federal government employees. 14. It is appropriate to swear at federal government employees. 15. It is inappropriate to show your middle finger to federal government employees. 16. It is appropriate to threaten federal government employees.	*Implicit Target* 1. It is appropriate to spit on people to make your point in political discussions. 2. It is appropriate to punch people to make your point in political discussions. 3. It is inappropriate to shove people to make your point in political discussions. 4. It is inappropriate to throw rocks to make your point in political discussions. *Politician Target* 5. It is appropriate to spit on politicians. 6. It is inappropriate to punch politicians. 7. It is inappropriate to shove politicians. 8. It is appropriate to throw rocks at politicians. *Opposing Partisan Target* 9. It is inappropriate to spit on [Democrats/Republicans]. 10. It is inappropriate to punch [Democrats/Republicans]. 11. It is appropriate to shove [Democrats/Republicans]. 12. It is inappropriate to throw rocks at [Democrats/Republicans]. *Government Target* 13. It is inappropriate to spit on federal government workers. 14. It is appropriate to punch federal government workers. 15. It is inappropriate to shove federal government workers. 16. It is appropriate to throw rocks at federal government workers.

Perceived Norms (N)	*Implicit Target* 1. Most people think it is okay to be uncivil when arguing about politics. 2. Most people think it is bad to swear when arguing about politics. 3. Most people think it is okay to show your middle finger to someone when arguing about politics. 4. Most people think it is bad to threaten someone when arguing about politics. *Politician Target* 5. Most people think it is bad to be uncivil towards politicians. 6. Most people think it is okay swear at politicians. 7. Most people think it is bad to show your middle finger to politicians. 8. Most people think it is okay to threaten politicians. *Opposing Partisan Target* 9. Most people think it is okay to be uncivil towards [Democrats/Republicans]. 10. Most people think that it is bad to swear at [Democrats/Republicans]. 11. Most people think it is okay to show your middle finger to [Democrats/Republicans]. 12. Most people think that it is bad to threaten [Democrats/Republicans]. *Government Target* 13. Most people think that it is bad to be uncivil towards federal government employees. 14. Most people think that it is bad to swear at federal government employees. 15. Most people think that is is bad to show your middle finger to federal government employees. 16. Most people think that it is okay to make threaten federal government employees.	*Implicit Target* 1. Most people think it is okay to spit on people when arguing about politics. 2. Most people think it is bad to punch someone when arguing about politics 3. Most people think it is bad to shove someone when arguing about politics. 4. Most people think it is bad to throw rocks at someone when arguing about politics. *Politician Target* 5. Most people think it is bad to spit on politicians. 6. Most people think it is okay to punch politicians. 7. Most people think it is bad to shove politicians. 8. Most people think it is okay to throw rocks at politicians. *Opposing Partisan Target* 9. Most people think it is bad to spit on [Democrats/Republicans]. 10. Most people think it is bad to punch [Democrats/Republicans]. 11. Most people think it is okay to shove [Democrats/Republicans]. 12. Most people think it is okay to throw rocks at [Democrats/Republicans]. *Government Target* 13. Most people think it is bad to spit on federal government employees. 14. Most people think that it is okay to punch federal government employees. 15. Most people think it is bad to shove federal government employees. 16. Most people think that it is bad to throw rocks at federal government employees.

Self-Efficacy (S)	*Implicit Target* 1. Incivility helps me make my point when arguing about politics. 2. Swearing helps me make my point when arguing about politics. 3. Showing my middle finger does not help me make my point when arguing about politics. 4. Threatening someone does not help me make my point when arguing about politics. *Politician Target* 5. Incivility helps me make my point when arguing with politicians. 6. Swearing does not help me make my point when arguing with politicians. 7. Showing my middle finger does not help me make my point when arguing with politicians. 8. Threats help me make my point when arguing with politicians. *Opposing Partisan Target* 9. Incivility does not help me make my point when arguing with [Democrats/Republicans]. 10. Swearing does not help me make may point when arguing with [Democrats/Republicans]. 11. Showing my middle finger helps me make my point when arguing with [Democrats/Republicans]. 12. Threats do not help me make my point when arguing with [Democrat/Republican]. *Government Target* 13. Incivility does not help me make my point when dealing with federal government employees. 14. Swearing helps me make my point when dealing with federal government employees. 15. Showing my middle finger does not help me make my point when dealing with federal government employees. 16. Threats help me make my point when dealing with federal government employees.	*Implicit Target* 1. Spitting on people does not help me make my point when arguing about politics. 2. Punching people helps me make my point when arguing about politics. 3. Shoving people does not help me make my point when arguing about politics. 4. Throwing rocks helps me make my point when arguing about politics. *Politician Target* 5. Spitting on a politician would help me make my point when arguing. 6. Punching a politician would not help me make my point when arguing. 7. Shoving a politician would not help me make my point when arguing. 8. Throwing rocks at a politician would help me make my point when arguing. *Opposing Partisan Target* 9. Spitting on a [Democrat/Republican] would not help me make my point when arguing. 10. Punching a [Democrat/Republican] would help me make my point when arguing. 11. Shoving a [Democrat/Republican] would not help me make my point when arguing. 12. Throwing rocks at a [Democrat/Republican] would help me make my point when arguing. *Government Target* 13. Spitting on a federal government employee would help make my point when dealing with them. 14. Punching a federal government employee would not help me make my point when dealing with them. 15. Shoving a federal government employee would not help me make my point when dealing with them. 16. Throwing rocks at a federal government employee would not help me make my point when dealing with them.

Appendix 5: Go-List to Select Social Content

Ago, Awesome, Beautiful, Bless, Boy, Call, Card, Care, Check, Cheer, Child, Class College, Color, Columbia, Crazy, Cuz, Date, Dear, Delta, Don't, Dream, Eat, Emily, Face, Fall, Fan, Favorite, Feel, Fight, Forever, Free, Friend, Game, Girl, Gotta, Group, Guess, Hand, Hard, Hear, Heart, High, Honor, I'm, Kapp, Kappa, Kelsey, Kid, Lady, Lamb, Life, Live, Long, Love, Lucky, Man, Memory, Message, Michael Brown, Missouri, Mizzou, Moment, Month, Mother, Move, MU, Music, Number, Officially, OMG, Perfect, Person, Photo, Picture, Play, Post, Practice, ProfHayley, Phi, Prom, Real, Realize, Remember, Sad, Season, Semester, Senior, Side, Sooo, Son, Spring, St., Stand, State, Stop, Student, Study, Support, Talk, Taylor, Team, Thing, Time, Tomorrow, Tonight, Trip, True, Turn, Ugh, Ur, Video, Volleyball, Vollyball, Wall, Wanna, Week, Weekend, Win, Woman, Work, World, Write, Wrong, www, Youtube

$N = 126$

VITA

Joshua Hawthorne was born on May 11, 1988 in Champaign, IL. He completed his Bachelor's degree in Communication from the University of Illinois in 2010. Josh then served as an AmeriCorps VISTA member for a year before coming to the University of Missouri to attend graduate school in 2011.

Josh completed his Master's degree in Political Communication from the University of Missouri in 2013 and stayed in the Communication Department to complete his doctoral program. He was able to complete his doctoral degree in record time (3 years!) because he took some extra classes during his Master's degree program and the timeline for the dissertation project was condensed. This project was completed in the summer of 2016. While in graduate school at the University of Missouri Josh has presented his research 30 times to local, regional, national, and international academic audiences. Also his work has been published 13 times in academic journals and books.

During his time in graduate school, Josh met his wife and they started a family together. Now, the Hawthorne family has departed for greener pastures in Illinois. Both Josh and his wife, Hayley, have accepted assistant professor positions at Monmouth College.