Start Spreading the (fake) News: The Role of Fear and Anger in the Formation and Dissemination of Conspiratorial Beliefs

A Thesis Submitted to the Degree of

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Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work.

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David Moore

To Bud & Zena

"You tell those people what to think, you've lost them.

But you tell them what to feel, they're yours."

- Russel Crowe as Roger Ailes, The Loudest Voice

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Of all the money that e'er I had
I spent it in good company - the Parting Glass

Summary

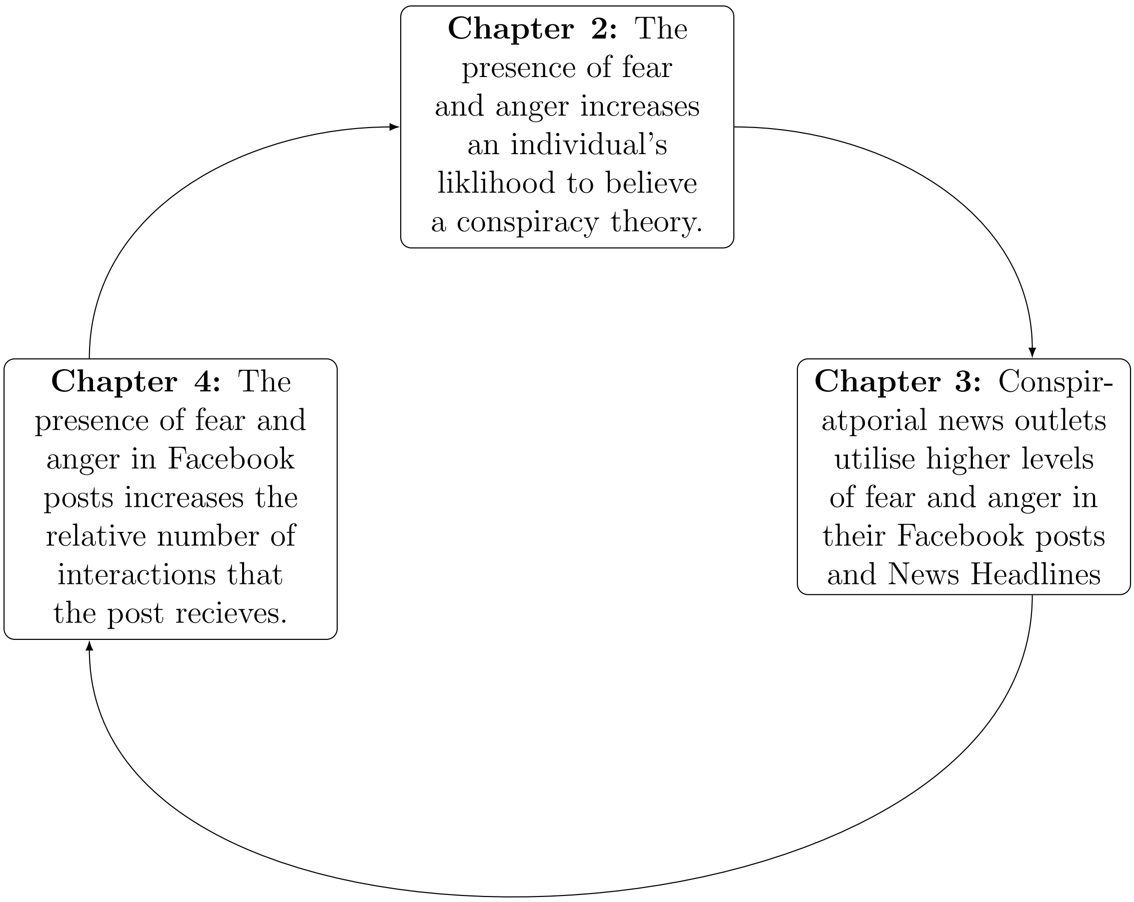
This dissertation investigates the influence that the presence of fear and anger in conspiratorial messaging has on the formation and dissemination of conspiratorial beliefs. Focusing on the United States of America, the study uses a combination of a framing experiment and quantitative text analysis to address the subcomponents of this causal relationship.

Chapter 2 uses a framing experiment to demonstrate that, unsurprisingly, individuals who are exposed to a conspiracy theory are more likely to believe that theory than those who are not exposed to the conspiracy theory. The chapter subsequently investigates whether this relationship is stronger when the individual is exposed to the conspiracy theory through a frame of fear or anger. That is, individuals who are exposed to a conspiracy theory through a frame of fear or anger are more likely to believe this theory than those exposed to the same conspiracy theory through a neutral frame. The Chapter fails to comprehensively demonstrate this relationship.

Chapter 3 explores whether or not news outlets that are known to propagate conspiracy theories (conspiratorial news outlets) are more likely to utilise fear and anger in their messaging than news outlets that do not propagate conspiracy theories (non-conspiratorial news outlets). This naturally follows the findings in Chapter 2. If the presence of fear and anger in conspirational articles increases an individual's propensity to believe in that theory then it is important to explore whether, in the real world, conspiratorial outlets utilise heightened levels of fear and anger in their messaging. This is explored using two newly created datasets. The first contains 7,221,509 Facebook posts. This represents the entire population of Facebook posts from the US news media from 01 January 2020 to 31 January 2021. The second dataset contains 180,175 news articles and headlines from nine right-wing news outlets in the United

States. Using quantitative text analysis this chapter demonstrates that conspiratorial news outlets utilise higher levels fear and anger in their Facebook posts and news headlines than non-conspiratorial outlets.

Figure 1: Thesis Flowchart



Finally, Chapter 4 analyses whether the presence of fear and anger in conspiratorial outlets Facebook posts increases the relative number of interactions (likes, comments, etc.) a post receives. This naturally follows from the results presented in Chapters 2 and 3. The presence of fear and anger increases an individual's propensity to believe in a conspiracy theory and conspiratorial outlets are more likely to utilise fear and anger in their social media posts and news headlines. Therefore, the final piece of the puzzle is whether this influences the dissemination of conspiracy theories online. Using the dataset of Facebook posts from Chapter 3, this Chapter demonstrates that the presence of fear and anger in conspiratorial outlets Facebook posts increases the number of relative interactions that the post receives.

As Figure 1 shows, Chapters 2, 3, and 4 work together to demonstrate the profound role that fear and anger plays in the formation and dissemination of conspiratorial beliefs. This dissertation demonstrates that:

1. fear and anger influence individuals perceptions of conspiracy theories;
2. conspiracy theorists utilise higher levels of fear and anger in their Facebook posts and news headlines
3. the presence of fear and anger in Facebook posts created by conspiracy theorists influences the interactions of these posts.

Thus, through these three linked investigations a more thorough understanding of the effect of fear and anger on conspiratorial beliefs is achieved.

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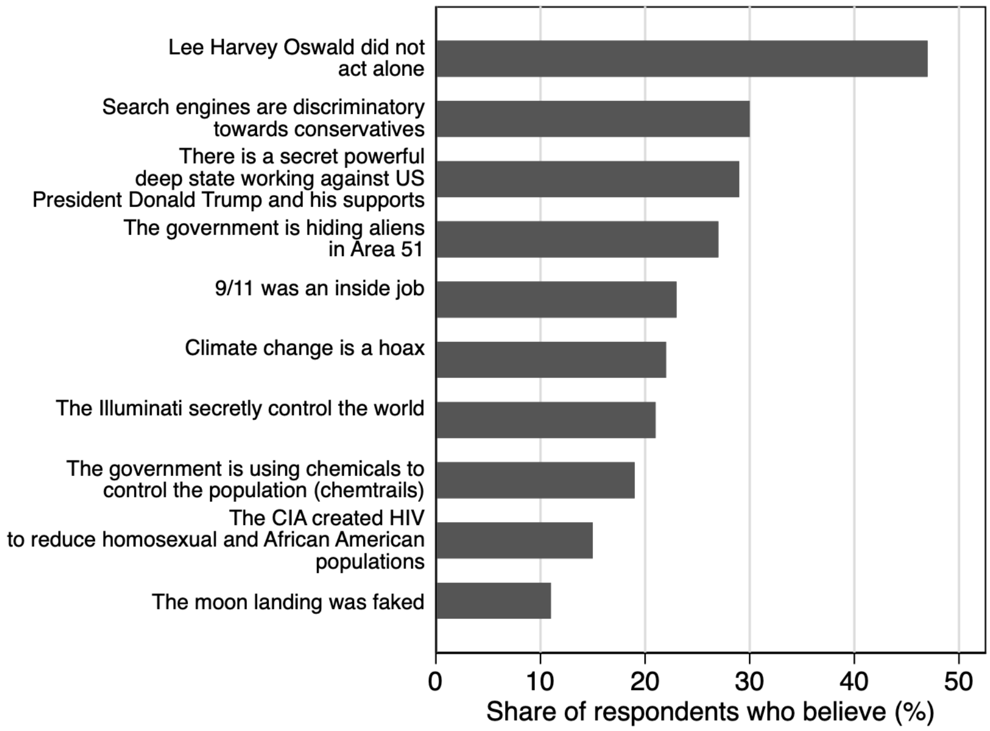
Chapter 1

Introduction and Motivation

1.1 Motivation

Conspiracy theories are often dismissed as inconsequential narratives and the absurd preoccupation of society's fringe. However, this misunderstands how widespread these beliefs are in society. Polls consistently show that a significant portion of American citizens believe in conspiracy theories. Between a quarter and a third of Americans are estimated to believe in some form of the 'Birther' conspiracy theory - that President Obama was not born in the United States. A similar number of Americans believe in the 'Truther' conspiracy theory - that the US government either orchestrated the September 11 attacks or at least knew about them in advance and did nothing to prevent them. As Figure 1.1 demonstrates, close to half of Americans believe that the assassination of President John F. Kennedy was orchestrated by conspiracy and covered up by the government (Uscinski & Parent 2014, Berinsky 2018). Indeed, some polls have this figure as high as 60 per cent (Enten 2017). There is not a single significant event in the world today that does not generate conspiratorial speculation. Whether that be an election result, an economic crisis, a terrorist attack, a political assassination, a military conflict, or a pandemic (Byford 2011).

Figure 1.1: Belief in Popular Conspiracy Theories (2019)



Source: Statista (*https://www.statista.com/statistics/959315/belief-in-conspiracy-theories-in-the-us/*)

It is estimated that between 50 and 63 per cent of Americans believe in at least one conspiracy theory (Seitz-Wald 2013, Oliver & Wood 2014). Republicans and Democrats are both likely to believe in widespread electoral fraud when their preferred candidate fails to win the Presidency. Conspiratorial ideology is far from a fringe activity with belief in conspiracy theories ubiquitous in American society (Hofstadter 1964, Uscinski & Parent 2014, Uscinski, Klofstad & Atkinson 2016). These beliefs permeate throughout society with research demonstrating those survey respondents who profess these beliefs are sincere (Berinsky 2018).

Conspiratorial beliefs need not pose danger to society or government nor necessarily do those who believe in conspiracy theories become dangerous or violent. Conspiracy theories are so widespread that if this were the case society would break down. Most conspiracy theories come and go with little fuss. While most of those that stand the test of time merely provide entertainment to people and remain harmless. Indeed, conspiracy theories by their very nature result in people questioning those in power. This can help increase transparency, reveal inconsistencies in official accounts of events, and may even reveal real conspiracies. The uncovering of many major political scandals such as the Watergate scandal, the Iran-Contra affair, and George W. Bush's public insistence that there were weapons of mass destruction in Iraq without evidence started as conspiracy theories. Unlike theories such as Birtherism and Trutherism, these conspiracy theories were true. Once proved these stopped being conspiracy theories and became conspiracies. Since elites do engage in conspiracy, conspiracy theories can be a crucial tool through which the powerful can be held accountable. It is possible to view conspiracy theories as an ingredient in democratic discourse. Indeed, some conspiracy theories genuinely raise issues in society that need to be addressed (Uscinski & Parent 2014).

Yet, despite the potential benefits of conspiracy beliefs they are also overwhelmingly been linked to harmful political, societal, and health outcomes. Throughout history conspiracy theories have been closely linked to prejudice, witch hunts, revolutions, and genocide. They have motivated terrorists, driven people to reject mainstream medicine, and led to a rejection of science. Belief in conspiracy theories has been demonstrated to increase partisanship, reduce public policy efficacy, political legitimacy, political engagement, institutional trust, harm public health, and increase the likelihood of political violence. Studies have shown that those who are exposed to conspiracy theories are less likely to vote in elections, are less likely to trust in political institutions, are less likely to seek the correct medical health, are more likely to reject mainstream science, and more likely to both view political violence as acceptable and engage in political violence (Douglas, Uscinski, Sutton, Cichocka, Nefes, Ang & Deravi 2019).

These negative consequences go beyond academic findings in survey and lab experiments. A conspiracy relating to genetically modified food produce led to several African countries banning the importation and harvesting of such foodstuffs. This had appalling consequences on some of the most malnourished regions of the world. Conspiracy theories relating to pharmaceutical companies and doctors influenced South African leaders to ban the use of certain HIV drugs. Over a third of a million people are estimated to have died as a direct consequence of this decision. Similarly in America, conspiracy theories about big pharma have caused HIV-infected individuals to be unwilling to seek the correct medical attention while similar sentiments have caused a decrease in the uptake of vaccinations and an associated increase in the incidence of several diseases (Uscinski & Parent 2014, Uscinski, Klofstad & Atkinson 2016, Uscinski 2018, Douglas et al. 2019, Uscinski 2020).

American history is full of examples of political violence resulting from conspiratorial beliefs. Race riots and red scares motivated by such beliefs caused incalculable damage to the country. The shoot-out at Ruby Ridge, Idaho came from the antagonism between law enforcement and conspiracy theorists. The Oklahoma City Bomber, Timothy McVeigh, believed the government was conspiring to violate civil liberties. In 1996, Eric Rudolph bombed the Centennial Olympic Park, two abortion clinics, and a gay bar in order to fight against the US government's advancement of socialism. Sympathisers to his cause managed to keep him hidden from law enforcement for over a year after the bombings. The Fort Hood shooter and the Boston Marathon bombers were both motivated by conspiracies that the US was conspiring against Muslims. More recently, the January 2021 insurrection and storming of the US Capitol was motivated by conspiracy theories relating to widespread election fraud pushed by then-President Donald Trump. This lead to five deaths and over 140 injuries. In Europe, Anders Behring Breivik's conspiratorial views led him to massacre 77 young Norwegians while the anti-Semitic stab-in-the-back myth that became popular in Interwar Germany helped the rise of the Nazis and ultimately contributed to the deaths of millions of people (Sunstein 2014, Douglas et al. 2019, Rakich, Rogers & Skelly 2021).

Once an individual believes in a conspiracy theory it is incredibly difficult to reverse that belief. Factors such as partisan bias and natural inclination towards a conspiratorial worldview explain some of this. Another important factor is motivated reasoning. Human beings do not wish to be proved wrong. We seek information that confirms our preconceptions, opinions, and biases. Therefore, corrective information is ignored and information that confirms what we already believe to be true is accepted. This is particularly true in the case of conspiracy theories where attempts to correct conspiratorial accounts of events are deemed to just be part of the cover-up. Furthermore, people who believe in one conspiracy theory are likely to then believe in others, even if they are unrelated or contradictory (Goertzel 1994, Wood, Douglas & Sutton 2012). Therefore, conspiratorial ideology begets conspiratorial ideology making the phenomenon even more dangerous. The fact that these opinions are so difficult to break and often spawn more conspiratorial beliefs means understanding how their formed is of the utmost importance.

1.2 The Characteristics of Conspiracy Theories

Conspiracy theories have received much attention in the political science literature (Goertzel 1994, Pipes 1999, Sunstein & Vermeule 2009, Byford 2011, Uscinski & Parent 2014, Oliver & Wood 2014, Brotherton 2015, Bilewicz, Cichocka & Soral 2015, Uscinski, Klofstad & Atkinson 2016, Douglas, Sutton & Cichocka 2017, Douglas et al. 2019). Despite this attention, there is still no universally accepted definition for conspiracy theories. Indeed, no necessary and sufficient conditions for conspiracy theories have been identified leaving the phenomenon somewhat ill-defined (Sunstein & Vermeule 2009).

The term conspiracy theory has become pejorative in nature and often serves to delegitimize opposing opinions (Coady 2006). They have been described as the paranoid style of American politics (Hofstadter 1964). While Noam Chomsky has noted that describing someone as a conspiracy theorist serves as a form of character assassination. Indeed, he described the use of the term as 'the intellectual equivalent of four-letter words and tantrums' (Chomsky 2004). Indeed, the Watergate and Iran-Contra scandals were initially dismissed as mere 'conspiracy theories' but turned out to be true (Byford 2011, Uscinski & Parent 2014). The official narrative to the 9/11 terrorist attacks points to a conspiracy perpetrated by Al Qaeda. In this sense, it was not a conspiracy by the Bush administration but by foreign actors. These factors all lead academics who study conspiracy theories to wonder, how can true conspiracies be separated from spurious conspiracy theories? There is agreement over the need to create a distinction between real and bogus conspiracies. However, within the academy, there is no consensus as to where the boundary between a 'conspiracy theory' and the legitimate exploration of real conspiracies (Byford 2011).

Before engaging in any systematic study of conspiracy theories a working definition of the phenomenon must be presented. In the broadest sense, a conspiracy theory is an explanation, either in the form of speculation or evidenced-based reasoning, which attributes the causes of an event to a conspiracy or plot (Byford 2011). However, in common parlance, the term 'conspiracy theory' tends not to focus on petty or obvious plots, or one with a straightforward or benevolent objective (Sunstein & Vermeule 2009, Byford 2011, Uscinski & Parent 2014, Bilewicz, Cichocka & Soral 2015, Brotherton 2015, Uscinski, Klofstad & Atkinson 2016). Indeed, conspiracy theories focus their attention on large scale, dramatic social and political events for explanations that do not merely describe or explain an event, but also expose some remarkable and hitherto unknown 'truth' about the world (Byford 2011). This is exemplified by the world's most famous conspiracy theories. For instance, the Bush administration orchestrated the 9/11 terror attacks, the Illuminati were behind the French Revolution, that the FBI were behind the assassination of JFK, and that there is a powerful and secretive group known as the New World Order conspiring to rule the world through an authoritarian government (Byford 2011, Uscinski & Parent 2014, Brotherton 2015).

For the purpose of this dissertation, the following definition will be utilized: *"a conspiracy theory is a secret arrangement between a small group of actors to usurp political or economic power, violate established rights, hide vital secrets,*

Table 1.1: Overview of Conspiracy Theories

1. What are they?	The belief that certain events or situations are secretly manipulated behind the scenes by powerful forces with negative intent.
2. Conspiracy theories have these 6 things in common	1. An alleged, secret plot. 2. A group of conspirators. 3. ‘Evidence’ that seems to support the conspiracy theory. 4. They falsely suggest that nothing happens by accident and that there are no coincidences; nothing is as it appears and everything is connected. 5. They divide the world into good or bad. 6. They scapegoat people and groups.
3. Why do they flourish?	They often appear as a logical explanation of events or situations which are difficult to understand and bring a false sense of control and agency. This need for clarity is heightened in times of uncertainty like the Covid-19 pandemic.
4. How do they take root?	Conspiracy theories often start as a suspicion. They ask who is benefiting from the event or situation and thus identify the conspirators. Any ‘evidence’ is then forced to fit the theory. Once they have taken root, conspiracy theories can grow quickly. They are hard to refute because any person who tries is seen as being part of the conspiracy.
5. How do they spread?	Most believe they are true. Others deliberately want to provoke, manipulate or target people for political or financial reasons. Beware: They can come from many sources e.g. internet, friends, relatives.

Source: The European Commission

https://ec.europa.eu/info/live-work-travel-eu/coronavirus-response/fighting-disinformation/identifying-conspiracy-theories_en *or illicitly cause widespread harm"* (Uscinski, Klofstad & Atkinson 2016). This definition is utilized as it focuses on the theories that relate to important social and political issues. A further extension to this definition is that theory must not have been proven wrong through official or reputable investigations (Byford 2011). The definition of conspiracy theories allows us to identify the relevant theories while the additional extension allows us to separate those that have been proven to be true. Table 1.1 outlines the European Commission's understanding of the characteristics of conspiracy theories

1.3 The Dangers of Belief in Conspiracy Theories

Conspiracy theories are often dismissed as the absurd preoccupation of society's fringe elements. Believed to be the sanctuary of the paranoid and the extreme (Hofstadter 1964, Byford 2011, Uscinski & Parent 2014, Uscinski, Klofstad & Atkinson 2016). However, as discussed earlier, this attitude overlooks the very real dangers that conspiracy theories pose to society with belief in conspiracy theories is ubiquitous in American society. Belief in conspiracy theories is far from a fringe activity in American society (Uscinski & Parent 2014, Bilewicz, Cichocka & Soral 2015, Brotherton 2015). The dangers that conspiracy theories pose to democratic states are best understood through three prisms: the democratic health of a state; public health; and political violence.

1.3.1 Conspiracy Theories and the Democratic Health of a State

Widespread belief in conspiracy theories amongst the populous can have a consequential negative impact upon the democratic health of a state. For instance, belief in conspiracy theories has been shown to increase political polarization, which, in turn, decreases public policy efficacy (Goertzel 1994).

Reduced public policy efficacy is further compounded by the fact that these theories must often be addressed by politicians. For instance, while overseeing a faltering economy that had just emerged from the worst economic downturn since the Great Depression as well as managing two wars, Barack Obama had to repeatedly address accusations that he had not been born in the United States and therefore was not eligible to be president of the United States. This culminated in President Obama convening a press conference where he released his long-form birth certificate. The 9/11 Commission was designed, in part, to address the conspiracy theories that President Bush and Vice-President Cheney were in some way involved in the terror plot. Similarly, much of the Clinton presidency was spent addressing various conspiracy theories including the alleged assassination of a colleague by the president (Uscinski & Parent 2014). The time and effort spent by politicians addressing conspiracy theories decreases public policy efficacy. Through both, the difficulties of operating efficiently in highly polarized environments as well as the resources needed to address these theories, the efficacy at which public policy can be undertaken is reduced. In conjunction with the lowering of institutional trust amongst the populous, this represents a serious threat to democratic health.

Belief in conspiracy theories reduces public trust in political institutions, lowers voters' willingness to engage in politics, undermines political legitimacy, increases partisanship and reduces public policy efficacy (Goertzel 1994, Byford 2011, Uscinski & Parent 2014, Bilewicz, Cichocka & Soral 2015, Brotherton 2015). All of these factors represent a real and serious threat to a state's democratic health.

1.3.2 Conspiracy Theories and Public Health

Conspiracy theories also represent a significant danger to public health. For example, the aforementioned conspiracy theories in Africa surrounding genetically modified foodstuffs and HIV drugs and the needless loss of life that resulted from these beliefs. It is estimated that this resulted in more than 300,000 South Africans dying needlessly from HIV as a result of the HIV drugs conspiracy theory (Uscinski & Parent 2014). This mentality is also observed in the United States where many African Americans, scarred by the Tuskegee Syphilis Study, refused treatment for HIV due to the belief that the drugs are ineffective and actually damage health (Brotherton 2015). Furthermore, anti-vaccination conspiracy theories have been attributed to a drop off in the rates of vaccinated children in the United States. This theory, which holds that childhood vaccinations can aid in the development of autism, has been widely discredited by the medical community. Indeed, the article that first cited this link has been retracted by the peer-reviewed journal that first published it and the doctor who lead the study was stripped of his medical license (Wakefield, Murch, Anthony, Linnell, Casson, Malik, Berelowitz, Dhillon, Thomson, Harvey et al. 1998, Brotherton 2015). Despite efforts to correct this misinformation vaccination rates have dropped due to fears over their supposed side effects (Brotherton 2015). This culminated in an outbreak of measles, a disease that, in the United States, had been all but eradicated, in California. Such theories based on little to no scientific evidence pose a serious risk to the public health of communities (Uscinski & Parent 2014). Of course, there were several conspiracy theories surrounding Covid-19 that made the fight against the virus more difficult than necessary. Ultimately, these theories range from the pandemic being faked/planned, that the virus was manufactured in a lab in Wuhan, that 5G masts cause one to contract Covid-19, that mask-wearing is unnecessary and is a form of elite control, as well as numerous conspiracy theories surrounding the Covid-19 vaccines. All of these theories have rendered it more difficult for the scientific and medical communities to limit the spread of the virus in the United States (Lewis 2020).

1.3.3 Conspiracy Theories and Political Violence

Finally, the belief in conspiracy theories has the potential to lead to political violence. Indeed, the United States has experienced several domestic terrorist attacks that were motivated by the belief in conspiracy theories. The Oklahoma City Bomber, Timothy McVeigh, attacked a federal building killing 168 and wounding hundreds more due to a belief that an overreaching government was determined to violate the rights afforded to American citizens by the US Constitution (Michel & Herbeck 2015). Eric Rudolph, who bombed the Centennial Olympic Park, Atlanta in 1996 as well as two abortion clinics and a gay bar believed that the American government was conspiring to advance abortion rights and worldwide socialism (Seegmiller 2007). Brothers, Tamerlan and Dzhokhar Tsarnaev, known as the Boston Marathon Bombers, were motivated, in part, because of a belief that the United States government was complicit in the 9/11 terrorist attacks (Starbird, Maddock, Orand, Achterman & Mason 2014). Infamously, part of the Nazi Party's ideology was the Stab in the Back Theory, which held that Germany did not lose World War I on the battlefield. Rather, it was civilians at home who surrendered, betraying the valiant efforts of the German soldiers (Uscinski & Parent 2014). In particular, this theory focused on Jews and Communists. This helped to stoke anti-Semitism in Nazi Germany, aiding in the occurrence of the Holocaust (Brotherton 2015). While this is far from an exhaustive list of political violence resulting from conspiracy theories it certainly highlights their destructive potential.

Belief in conspiracy theories need not always have such disastrous consequences. However, as outlined in the literature and the contemporary examples, conspiracy theories have the potential to increase partisanship, reduce public policy efficacy, political legitimacy, public engagement in the political process, and institutional trust, harm public health, and increase the likelihood of political violence. Each of these outcomes by themselves poses a grave danger to a state.

When taken together there is little doubt that conspiracy theories are extremely harmful to the health, safety, and social cohesion of a democratic state.

1.4 Why Do People Believe in Conspiracy Theories?

The literature on why people believe in conspiracy theories has been growing in recent years. In the past, through tools such as survey data, political and social scientists were able to point to who is more likely to believe conspiracy theories in general, and more specifically, who is more likely to believe specific conspiracy theories. The results of these studies showed that, in general, belief in conspiracy theories transcend gender, race, political ideology, and social class. Indeed, most groups were susceptible to different conspiracy theories (Brotherton 2015). For instance, African Americans are more likely to believe that crack cocaine was manufactured by the United States government to undermine their community (Pipes 1999). On the other hand, conservatives are more likely to think that Barack Obama was not born in the United States and, therefore, had no legitimate right to the presidency of the United States (Enders & Smallpage 2018). Further, the conspiracy theory that childhood vaccinations are linked to autism is subscribed to by both the far right and the far left in the United States (Brotherton 2015). Conservatives are more likely to believe that a powerful and secretive group known as the New World Order is conspiring to rule the world through an authoritarian government. However, there are people on the far left who also believe in this theory (Parsons, Simmons, Shinhoster & Kilburn 1999, Briones, Nan, Madden & Waks 2012, Uscinski & Parent 2014). Interestingly, evidence also suggests that in the United States those who support the party that holds the presidency are less likely to subscribe to conspiracy theories than those who support the opposition party. This is because wining groups feel less anxious and more in control and thus feel less of a need to explain the world through the prism of conspiracy theories (Bilewicz, Cichocka & Soral 2015). Evidence also points to a correlation between lower levels of education and the likelihood to believe in conspiracy theories (Douglas, Sutton, Callan, Dawtry & Harvey 2016) This has correlation is perhaps caused by a lack of training in analytical thinking as well as an increased likelihood to overestimate the co-occurrence of events (Brotherton & French 2014, Douglas, Sutton & Cichocka 2017).

More recently, greater interest has been paid to the psychological factors that might underpin belief in conspiracy theories. Some research has focused on an innate susceptibility to conspiracy theories, known as conspiratorial predisposition (Uscinski, Klofstad & Atkinson 2016). Other literature sites the relationship between the belief in the supernatural of paranormal and belief in conspiracy theories (van Prooijen, Douglas & De Inocencio 2018). In their review of the psychological research on conspiratorial beliefs Douglas, Sutton, and Cichocka (2017) noted that people seemed to be drawn to conspiracy theories when, compared with non-conspiratorial explanations of events, they satisfied three social psychological motives. These motives are epistemic (the desire for understanding, accuracy, and certainty), existential (the desire for safety and control), and social (the desire to maintain a positive image of the self or the group).

1.4.1 Epistemic Motives

As noted earlier, there is barely a major world event that is not accompanied by a host of conspiracy theories. When major events occur, people want answers. There is an inherent randomness to real-life events, especially major events such as assassinations, terrorist attacks, plane crashes, and war. Individuals do not like such randomness. Finding causal explanations for these events helps to build a stable, internally consistent and perceived accurate account of the world around us (Douglas et al. 2016, Douglas, Sutton & Cichocka 2017, Douglas et al. 2019). Attributing these events to the motives of people conspiring in secret to undermine the good of society can be easier to accept than the randomness of events. Further, these explanations can also allow us to keep our already held beliefs (e.g., climate change is a hoax). Indeed, belief in conspiracy means we need never change our opinion on a matter. Any contradictory evidence is simply part of the cover-up. Thus, belief in conspiracy theories provide broad, and consistent explanations for events that also allow them to maintain their beliefs in the presence of uncertainty (Douglas, Sutton & Cichocka 2017).

1.4.2 Existential Motives

In conjunction with epistemic motives, the causal explanations that conspiracy theories provide also help people to feel safe and secure in their environment, a fundamental psychological need. In this sense, identifying and ousting those involved in the conspiracy (for example, protesting against Joe Biden 'stealing' the Presidential election) allows people to feel that they are neutralising the threat posed by conspirators (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019). The research points to this conclusion through several findings. Studies show that people are more likely to turn to conspiracy theories when they feel anxious, feel powerless, and/or do not feel in control (Abalakina-Paap, Stephan, Craig & Gregory 1999, Bruder, Haffke, Neave, Nouripanah &

Imhoff 2013, Greszki, Meyer & Schoen 2014, Uscinski & Parent 2014, van Prooijen & Acker 2015, Douglas, Sutton & Cichocka 2017, Douglas et al. 2019).

1.4.3 Social Motives

For many of us the information we hold to be true is motivated by the desire to maintain a positive image of the self and the in-group. Conspiracy theories allow us to blame others for negative outcomes. Thus, conspiracy theories allow us to maintain the positive image of self and group. There are two sides to this. The valorization of the in-group and the demonisation of the out-group (Uscinski & Parent 2014, Douglas, Sutton & Cichocka 2017). For instance, blaming widespread fraud on an electoral victory explicitly states that your preferred candidate should have won under fair circumstances and that the political; opponent nefariously stole the election. Indeed, for those who believe Donald Trump to be the real winner of the 2020 Election, Mr Trump is a hero whereas Mr Biden conspired to steal the election against the will of the American people. This certainly sates the ego of both the self and the group. Many conspiracy theories fit this valorization/demonisation nexus. The demonisation of Jews has often gone hand in hand with anti-Semitic conspiracy theories. While polling demonstrates that 9/11 Truther conspiracy theories are popular in the Middle East with people refusing to accept fellow believers of Islam as the perpetrators. The belief by some African Americans that both the crack epidemic and the HIV pandemic were created by the government to reduce African American populations fulfils this psychological need.

1.5 Emotion and Public Opinion Formation

The role that emotion plays in politics was largely under studied in the political science and political psychology literature until the mid 1990s. While there was the sporadic publication of political science publications on emotion prior to the 1990s, the area received little overall attention. Indeed, seminal handbooks on the political psychology, such as, *A Source Book for the Study of personality and Politics* (1971) and *Political Psychology* (1986), do not contain a chapter on the role that emotion plays in politics . The reason for the relative lack of examination into emotions in politics was twofold. First, and most straightforward, there was a prevailing belief that emotion was mysterious and elusive and did not lend itself to scientific investigation. Second, the social sciences, then as now, were guided by Enlightenment precepts. That is, the growth in scientific reasoning and widespread education, would lead humans to rely more and more on reason and logic and less and less on emotions (a normatively destructive tool through which to evaluate situations). However, emotion has proved to be of enduring relevance to human life and critical to how humans see the word around then. Since the mid 1990s scholarship on emotion has appeared at an accelerated rate (Brader & Marcus 2011, Brader & Marcus 2013, Marcus, Valentino, Vasilopoulos & Foucault 2019, Marcus 2021).

Political science and political psychology have applied three models of emotion to theories of political behaviour and political judgement over the past seventy years. The oldest is the attitude theory, followed by cognitive appraisal theories, and finally the affective intelligence theory of emotion.

The Attitude Theory presented emotion along, with cognitive and behavioural, as one of the three components within attitude. The central claim made by attitude theory is that affective reactions can be treated as a single dimension that signals whether it is best to approach or to avoid a stimulus. That evaluation necessarily follows from what we know. therefore the emotion component of attitude theory comes (Marcus, Valentino, Vasilopoulos & Foucault 2019).

Cognitive Appraisal Theories propose that emotions existing along many different discrete states. These discrete states included anger, fear, hope, happiness, etc.. There are several versions of this theory, generally disagreeing as to how many discreet emptions exist, ranging from lows of seven or eight to highs over more than 22. Importantly, cognitive appraisal theorists tended to presume that an individual would usually predominantly experience one emotion at a time. The theory generally assumes that upon exposure to a stimulus, the exposed individual determines if the stimulus is positive or negative; then, certain or uncertain; controllable or not, and so on. Thus, emotion flows from a sequence of cognitions (Marcus et al. 2019).

Affective Intelligence Theory (AIT) represents the broadest and best known model of emotion and politics. AIT suggests that there are two basic emotional systems that monitor our environment and allocate out neural resources in accordance with our needs. The first, the disposition system, replies on learned routines to provide feedback about our current situation. These feedbacks are emotional in nature and range from enthusiasm to depression for habits that can provide rewards as well as varying levels of aversion when the habits can provide punishment. The second system, the surveillance system, influences our actions based on the novelty of the situation. The primary emotions range from calm to anxiety (Marcus et al. 2019). AIT focuses on our subconscious reaction to our surroundings based on habit and familiarity. This is distinct from the previous theories, which were more deliberative and conscious in nature (Brader & Marcus 2011, Brader & Marcus 2013, Marcus, Valentino, Vasilopoulos & Foucault 2019, Marcus 2021)..

The literature demonstrates that different emotions or “families of emotions” have distinct effects upon individuals. These effects do not always fit neatly into one particular theory. Instead these are what have been observed across multiple studies in the literature. There are eight basic emotions, as identified by Psychologist Robert Plutchik. These are anticipation, surprise, trust, joy, anger, fear, sadness, and disgust (Plutchik 1991).

Fear is the most studied emotion in the social sciences. The terms fear and anxiety (as well as alarm, worry, and terror, amongst others)generally refer to the same emotion. At most, these different terms convey offering intensities of the same emotion. Within clinical psychology and neurological research some researchers have drawn distinctions between these emotions. However. most political psychologists use the terms interchangeably (Brader & Marcus 2013). Therefore, for the purpose of this dissertation the term *fear* will be used as the catch-all phrase for these emotions.

Fear is a product of an emotional known as the 'surveillance system'. This system monitors the environment for potential threats and adapts behaviour accordingly. Fear interrupts and redirects attention and other cognitive activity towards dealing with the perceived threat. Fear prompts individuals to seek out information related to the perceived threat. The literature on the impact that fear has on memory is somewhat mixed. There is evidence presented that fear both improve and interfere with our recall (Brader & Marcus 2013). However, recent research has demonstrated that when exposed to new information in a heightened sense of fear are more likely to take on board that new information (Marcus et al. 2019). Fear has been shown to have a profound impact upon political opinion. For example, the fear caused by a terrorist attack can change voting intentions (Marcus et al. 2019). Similarly, negative politics is often based on stoking up fear at what a particular candidate would do in power (Wodak 2015). Research demonstrates that fear of potential negative consequences motivates people to fall for seemingly obvious scams online (Bradbury 2012). However, there is not consensus within the academy. Some research demonstrates that fear is not is not an explanatory factor in people supporting far-right parties and policies. While other research indicates that far-right populist discourse is the 'politics' of fear. Further, recent research into the Covid-19 pandemic demonstrated that increased levels of fear over the virus increased trust in government (Erhardt, Freitag, Filsinger & Wamsler 2021). Thus, while the literature indicates that fear has a strong impact on opinion formation it does seem that the context in which the fear is experienced and how it is directed is also important.

Anger - Although people experience anger as a distinct emotion to fear, the two are often reported together and appear to operate in proximity. Indeed, many of the same situations appear to produce both fear and anger. Nevertheless, the literature has provided distinctions between the two. Anger has been identified as both an approach and an aversion emotion. That is, unlike fear, anger motivates one to confront the cause of the emotion (whereas fear leads to avoidance). In this sense, fear and anger are similar in valence and arousal, but differ in the responses they engender (Giles, Horner, Anderson, Elliott & Brunyé 2020). However, anger is also an aversion emotion meaning that it causes such intense dislike that one is likely to avoid what causes the anger. In politics this is often seen as voting against policies or politicians that anger you (Marcus et al. 2019). Research demonstrates that angry citizens are less responsive to changing their prior convictions are are less receptive to new considerations or opposing views (Brader & Marcus 2013). However, anger also motivates people to engage more with these prior beliefs and can lead to political extremism (Marcus et al. 2019, **?**). That is, anger can re-enforce existing political beliefs leading to the development of more extreme opinions.

Disgust - While the literature somewhat struggles to disentangle fear and anger, the separation of disgust and anger proves even more complicated. The co-occurrence of individuals self-reporting of both anger and disgust is high while some studies use disgust as as indicator term when constructing scales for anger. It seems that disgust is much more associated with the senses. For example, seeing a decaying body or smelling urine in an alleyway. Disgust motivates people to stay away from noxious or impure stimuli. The effect of disgust on public opinion is not as well-studied as fear and anger. However, some studies examining disgust seem to point to a similar relationship to that of anger. For example, those pushing anti-immigration policy often use language inciting both anger and disgust to achieve the same end - reduced immigration levels (Brader & Marcus 2013).

1.6 Dissertation's Theory and Hypotheses: Emotion and Belief in Conspiracy Theories

The literature holds that conspiracy theories are likely to have emotional underpinnings. This is because belief in conspiracy theories seems to be associated with System 1 processes (Douglas, Cichocka & Sutton 2020). These processes are fast, automatic, and intuitive. As seen in the AIT model of emotional response to stimuli, this is similar to how information is processed while in a heightened emotional state (Douglas, Cichocka & Sutton 2020). Indeed, there is evidence that people in heightened emotional states may be susceptible fo conspiracy theories (Whitson, Galinsky & Kay 2015).

The literature also notes that fear and anger may increase a person's susceptibility to conspiracy theories as they heighten one's sense they they lack control or are unsafe in their environment. While conspiracy theories may not actually help individuals who feel these existential psychological motivations, these individuals are more likely to be susceptible to conspiratorial messages (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). Furthermore, the process of believing in conspiracy theories closely resembles the nature of information processing when in a heightened emotional state, that is, fast, automatic, and intuitive. Further, the use of negative emotions such as fear and anger also makes intuitive sense in the context of conspiracy theories. Conspiracy theorists are not trying to build something up or convince of its merits. They are trying to tear down or undermine existing institutions. Therefore, negative emotions that engender negative attitudes naturally make sense in this context. There is some research that supports the idea that conspiracy beliefs are underpinned by emotional states (Whitson, Galinsky & Kay 2015, Klein, Clutton & Dunn 2019). However, the area remains understudied.

Belief in conspiracy theories is, at least theoretically, strongly rooted in negative affect (van Prooijen & Douglas 2018). Anecdotal evidence suggests that conspiracies gain influence by eliciting negative emotions. In particular, the literature cites fear and anger (Fong, Roozenbeek, Goldwert, Rathje & van der Linden 2021). For example, McCarthyism and the 'Red Scare' painted Communists as a dangerous 'other' and constructed a culture of fear in America (Skoll & Korstanje 2013). This climate of fear convinced people of the realness of McCarthy's claims and led to widespread belief in the conspiracy theory. Anger, on the other hands, leads to increased engagement with conspiracy theories, influencing people's likelihood to believe in the theory and also influencing the spread of conspiracy theories (Mitra, Counts & Pennebaker 2016).

In the context of the psychological motivations underpinning conspiracy belief, the relationship between emotion and conspiracy seems to fit. Negative emotions such as fear and anger are highly related to feelings of threat, uncertainty, and negative opinions of out-groups. While it makes theoretical sense that there be a relationship between negative emotions and conspirational belief, to date there has been insufficient research in this area. The link has been noted in several studies. However, many of these papers are theoretical in nature and there has yet to be a thorough and systematic study of the relationship.

Despite these observations, the theoretical expectations, and the limited quantitative analyses to date, a thorough systematic study of the relationship between conspiracy theories and negative emotions such as fear and anger is lacking. Therefore, this thesis explores the following three interrelated hypotheses:

Hypothesis 1.1 *As the level of fear and anger within a conspiratorial message that an individual is exposed to increases so too does the likelihood of that individual believing in that conspiracy theory.*

Hypothesis 1.2 *Compared with non-conspiratorial news outlets, conspiratorial news outlets are more likely to use fear and anger in their Facebook posts, news articles, and news headlines.*

Hypothesis 1.3 *As the level of fear and anger within a conspiratorial news outlet's Facebook posts increases so too does the relative performance of the Facebook post.*

That is:

1. individuals are more likely to believe the conspiracy theory being presented to them if it is done so through a frame of fear or anger;
2. conspiratorial news outlets (i.e., news outlets that are known to spread conspiracy theories) are aware of this relationship and utilise higher levels of fear and anger in their messaging; and
3. given the effectiveness of fear and anger on conspiratorial belief as demonstrated in Hypothesis 1.1, heightened levels of fear and anger boosts conspiratorial outlet's Facebook posts, holding all else equal.

These hypotheses are investigated through an analysis of conspiracy theories within the United States news media ecosystem.

1.7 Case Selection - Why Fear and Anger

This dissertation's focus on fear and anger as the emotions of interest is three-fold.

1. While other negative emotions such as disgust, are mentioned in the literature, fear and anger are overwhelmingly cited in the literature as both being of theoretical importance and being widely observed in the world of conspiracy (van Prooijen & Douglas 2018). While much of the connection between these emotions remains theoretical and much of the observations of these emotions are anecdotal in nature, they are certainly the emotions most widely connected with the belief and dissemination of conspiracy theories. Therefore, they are of particular importance;

2. While the literature does differentiate between disgust and anger, it does acknowledge that the emotions are highly related (Brader & Marcus 2013). This can be seen through recent investigations into fear and anger in politics that did not also include disgust (Marcus 2021). Given the similarities and difficulty in separating anger and disgust as well as the important role the literature places on anger a decision was made to include anger rather than disgust; and

3. Chapter 2 of this dissertation presents a framing experiment. This experiment incurred significant financial costs. Given points 1 and 2 above, it was decided that the limited resources available to the researcher should be focused on fear and anger, rather than diluting the power of the farming experiment.

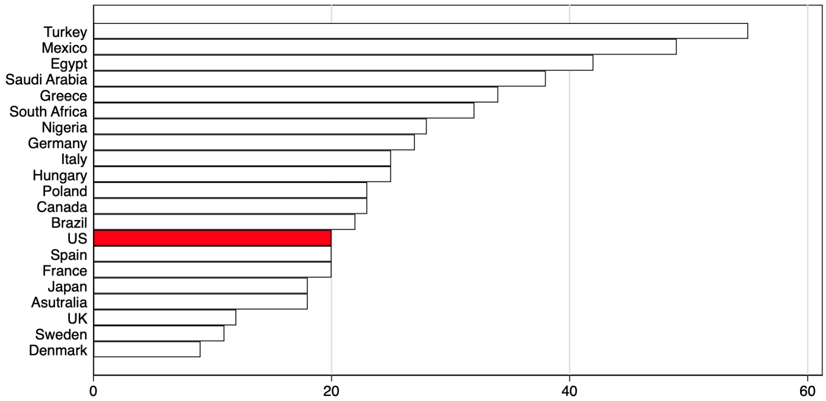
1.8 Case Selection - Why the United States in 2020?

To examine the relationship between fear, anger, and conspiracy theories, this dissertation analyses the effect that fear and anger have on conspiracy theories within the United States in 2020 as a case study of how this causal mechanism works. There are four reasons why the United States in 2020 makes a good case study for any investigation into conspiracy theories. The first two reasons relate to the country itself while the second two reasons relate to the unique year of 2020. First, as outlined in section 1.1, belief in conspiracy theories is ubiquitous in American society. Second, the United States has unique constitutional protections for both freedoms of speech and the media. Third, in 2020 the Covid-19 pandemic led to a surge in conspiracy theories. Lastly, Donald Trump and the Republican Party's efforts to undermine the results of the 2020 US Presidential Election via an array of conspiracy theories also led to a surge in conspiratorial beliefs in the country.

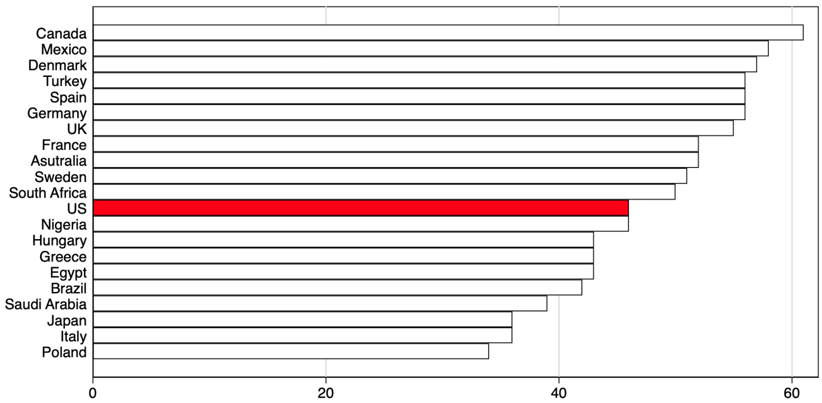
1.8.1 America and Conspiracy Theories - A Unique Relationship

As Uscinski and Parent (2014) note, the United States of American exists because of a conspiracy theory. American elites suspected that King George was conspiring to strip the colonists of their liberty and rule over them with absolute authority. If such a conspiracy theory sounds familiar it is because it is the same general motivations given to most of modern day's supposed conspirators. The Bush administration was behind 9/11 in order to strip Americans of their liberties. The same goes for other false flag events like Sandy Hook. There is a Deep State and/or a New World order conspiring to strip Americans of their liberties and rule with absolute authority. Indeed, the Covid-19 pandemic was planned to achieve the same aims. Conspiracy theories in the United States have existed since the founding of the state. So much so, that while Edmund Burke was sympathetic to the colonists he also observed that while other countries complained under an actual grievance, Americans anticipated their grievance and complained before they suffered (Uscinski & Parent 2014).

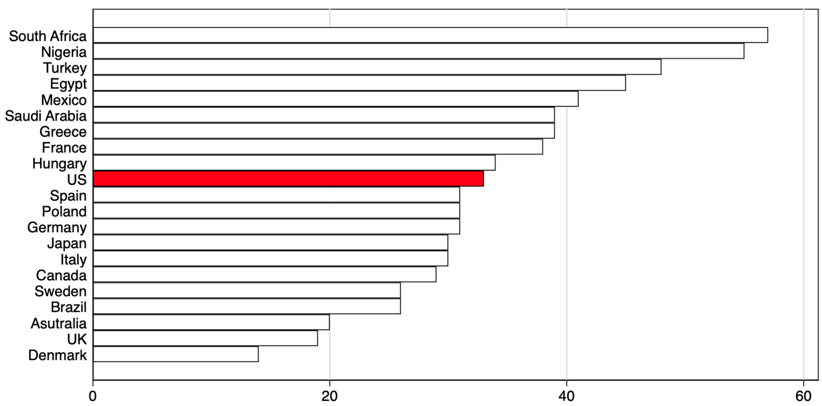
Figure 1.2: Multinational Conspiracy Beliefs



(a) 9/11 - Inside Job

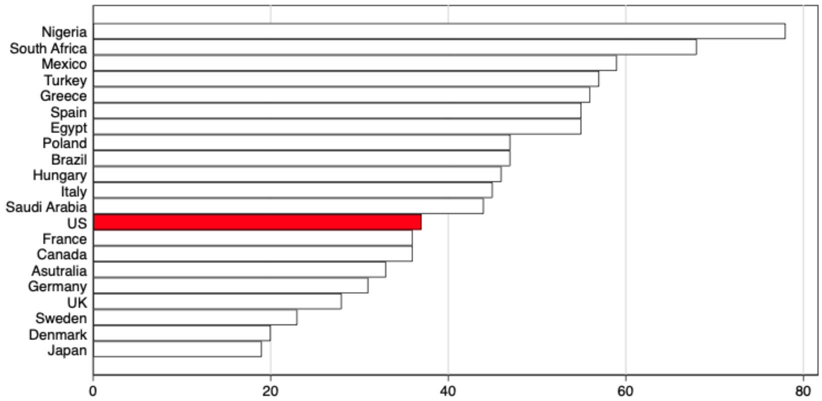


(b) Trump/Russia Collusion

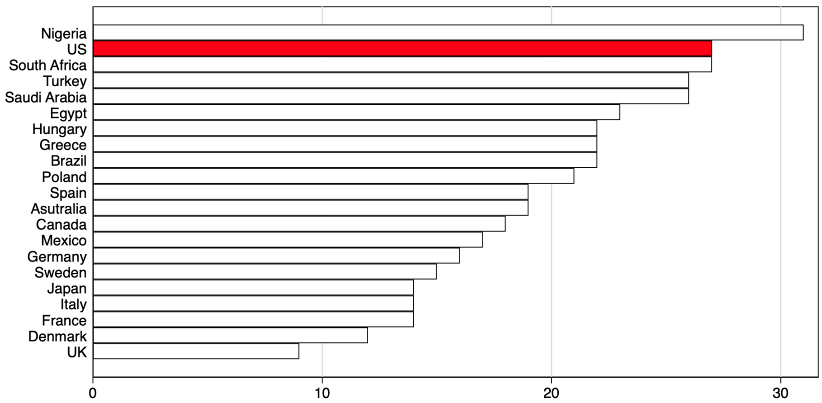


(c) Vaccinations

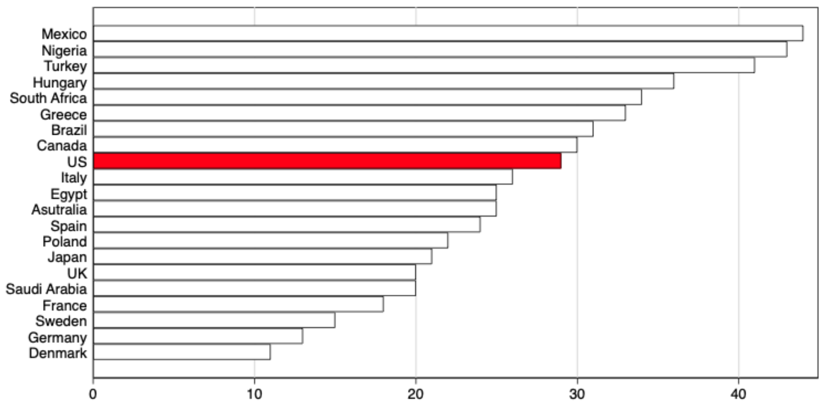
Figure 1.2: Multinational Conspiracy Beliefs(continued)



(d) New World Order

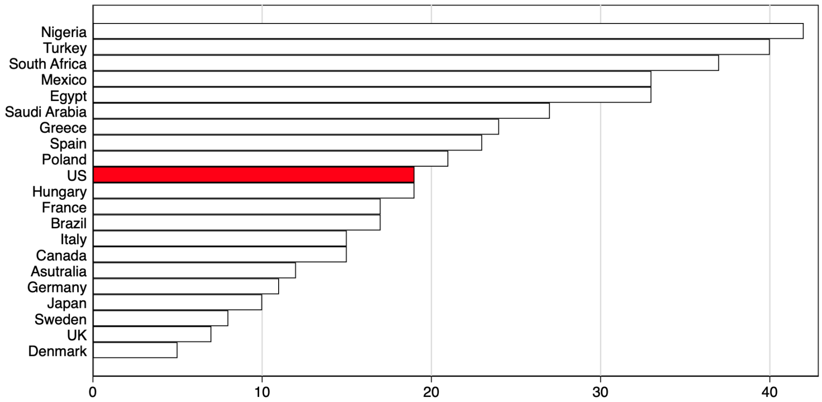


(e) Climate Change

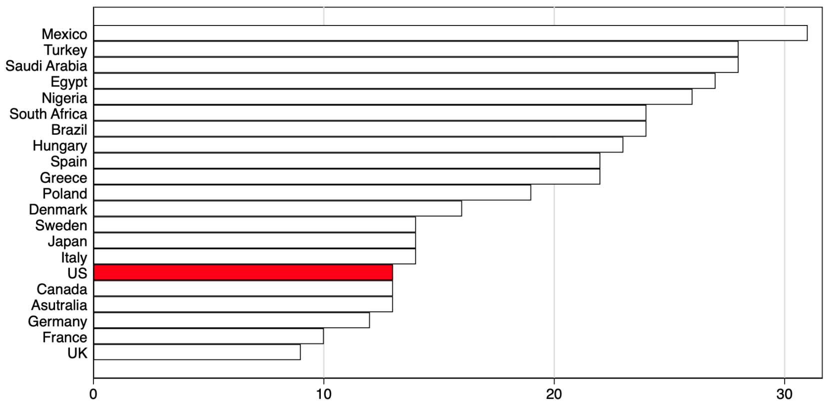


(f) Aliens

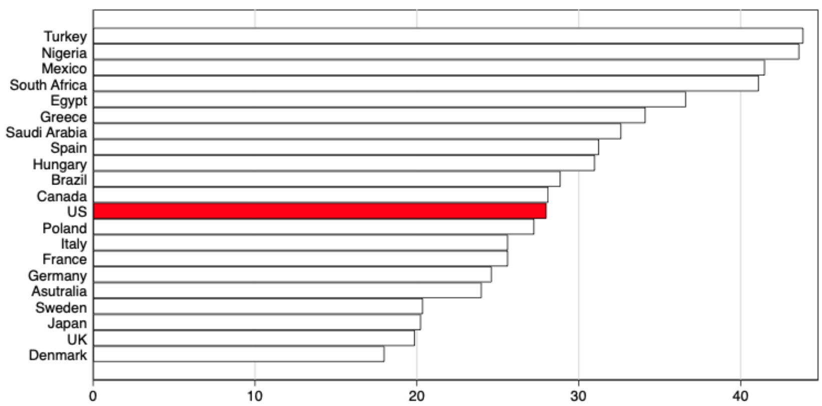
Figure 1.2: Multinational Conspiracy Beliefs(continued)



(g) HIV/AIDS



(h) Moon Landing



(i) Average Response

Source: You-Gov Cambridge Globalism Project 2020

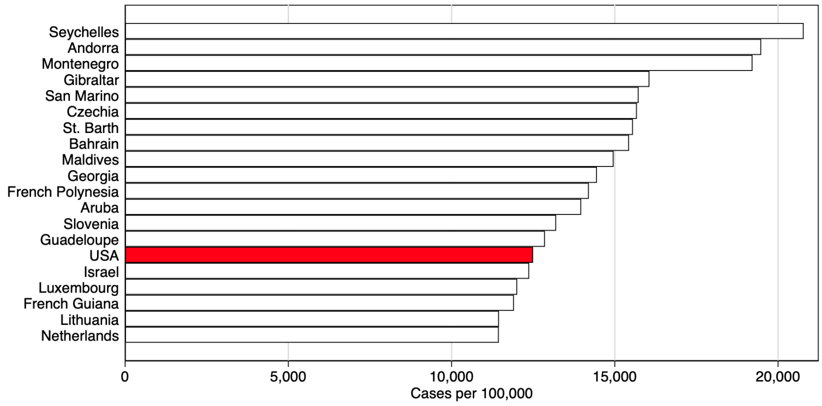
(https://yougov.co.uk/topics/international/articles-reports/2021/01/18/global-where-believe-conspiracy-theories-true)

Of course, conspiracy theories are not unique to the United States. As polling undertaken by the YouGov-Cambridge Globalism Project and displayed in Figure 1.2, different conspiracy theories enjoy varying popularity across a vast array of countries. However, when accounting for factors such as educations levels, development, presence of democracy, and group narcissism the US ranks quite high amongst the countries that consistently believe in various conspiracy theories, ranking joint twelfth and joint first in the English speaking world (see Figure 1.2(i)).

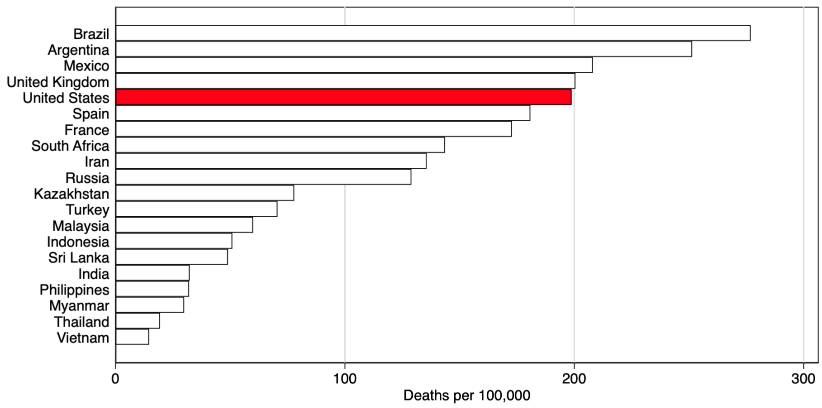
There is also some evidence that Americans' unique relationship to freedom of speech and the press may bolster conspiracy ideology in the country. Many conspiracy theories are libellous in nature. They often allege individuals have undertaken heinous acts that undermine the good of the people. In certain countries, some of these claims could not be published. However, the First Amendment of the US Constitution grants special privileges to both freedom of speech and freedom of the press. The relative power of the press in the United States is far greater than in very similar countries like the United Kingdom. It has been noted that while this structure may not directly lead to belief in conspiracy theories it certainly gives them the platform to spread relatively unhindered (Filvaroff 1972). Thus, the US offers a case study that may allow one to see a less obscured version of the true nature of conspiracy theories.

While belief in conspiracy theories is not unique to the United States, the country certainly has a long and decorated history with the phenomenon. The fact that such a relationship exists while not being an outlier means the United States offers a generalisable case study for any study on conspiracy theories.

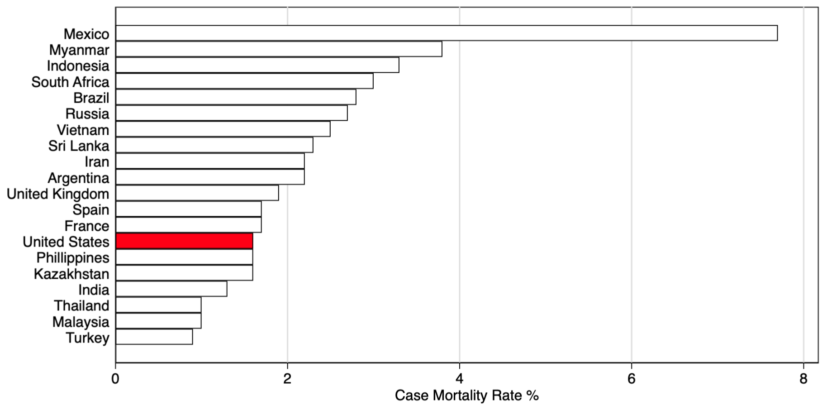
Figure 1.3: Covid-19 Cases and Deaths



(a) Cases



(b) Deaths



(c) Mortality Rate

Source: John Hopkins [a] *& Worldometer*[b]

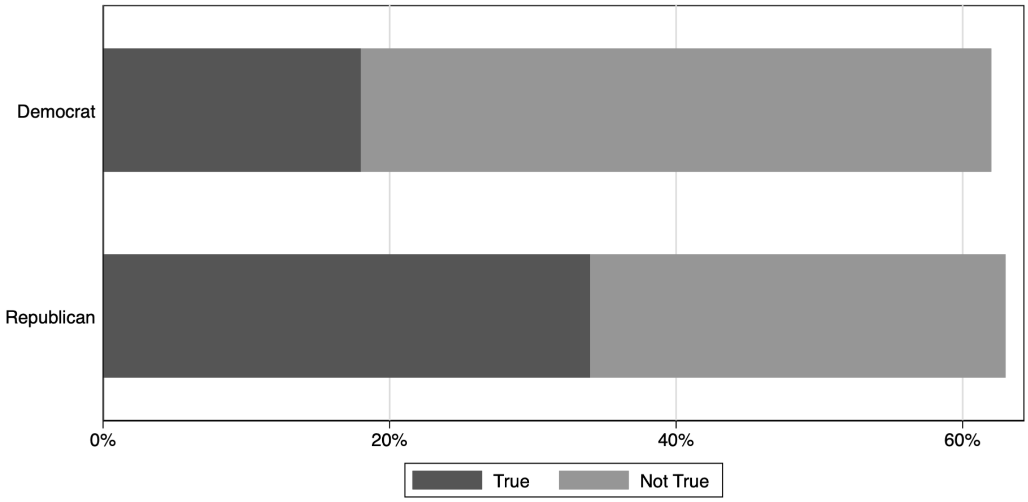
[a]`https://coronavirus.jhu.edu/data/mortality`
[b]https://www.worldometers.info/coronavirus/

1.8.2 2020, Covid-19, Conspiracy Theories, and Public Health

The United States is the fifteenth richest country in the world as measured by GDP per capita (World Bank 2021). It spends the most per capita on healthcare in the OECD, nearly $4,000 per person per year more than the second-highest spenders, Switzerland (OECD 2021). Yet, as Figure 1.3 demonstrates The United States has the fifteenth highest number of cases of Covid-19 per 100,000 of population in the world. Further, the US has the fourth-highest death toll from the virus per 100,000 of population and the fourteenth worst-case mortality rate (the per cent of cases that result in death). Importantly, several of the countries with a higher caseload than the US have such small populations that small numbers of cases can greatly increase their cases per 100,000. Therefore, given the resources at its disposal, the United States has had one of the worst global responses to the Covid-19 pandemic. There are several reasons for this. First, many in the United States place a high value on personal freedoms and individual liberty which has helped hinder the implementation of public health measures such as mask mandates and stay at home orders. Second, the decentralised nature of government meant a unified response was almost impossible. Third, inequalities in healthcare and outcomes left large portions of the population very vulnerable to the virus (Fitzpatrick & Wolfson 2020, Yong 2020).

While the US may have always been more vulnerable to a pandemic than other developed countries because of systemic factors, conspiracy theories also played a large role in the countries substandard response to Covid-19. In particular, then-President Trump, prominent Republicans, and right-wing media played down the pandemic, recommended alternative health therapies, and peddled in conspiracy theories. For example, initially, Donald Trump and his supporters either underplayed the severity of both the disease and the situation in the country. They often cited conspiracy theories such as Democrats and the media overplaying the severity of Covid-19 in order to undermine Trump's re-election chances instead of acknowledging the severity of the public health situation in the country (Fitzpatrick & Wolfson 2020, Yong 2020).

Figure 1.4: Was Covid-19 Planned?



Source: Pew Research Centre *(https://www.pewresearch.org/fact-tank/2020/07/24/a-look-at-the-americans-who-believe-there-is-some-truth-to-the-conspiracy-theory-that-covid-19-was-planned/)*

While Trump himself did not always directly engage in conspiracy theories relating to the virus, many within the right-wing media system did. These ranged from masks not being necessary, to the theory that the virus was created in a lab in Wuhan, that the pandemic was planned for population control purposes, that 5G was responsible for the virus, and that the pandemic was simply fake. All of these theories influenced the extent to which people followed public health advice (Uscinski, Enders, Klofstad, Seelig, Funchion, Everett, Wuchty, Premaratne & Murthi 2020). As Figure 1.4 demonstrates approximately 35 per cent of Republicans and 18 per cent of Democrats believe that the pandemic was planned.

Despite factors such as the initial surge of cases in New York and population density cases and deaths per 100,000 were worse in right-leaning states. Figure

1.5 shows a map of the Republican vote share in the 2020 Presidential Election while Figures 1.6(a) and 1.6(b) show the cases and deaths per 100,000 across the country respectively. The vote share and the cases per 100,000 map onto each other quite well with a positive correlation of 0.65. The relationship is not as strong for deaths per 100,000. However, there is a positive correlation of 0.20. Of course, there are cultural and systematic reasons that may explain some of this disparity in public health outcomes across Republican and Democratic states. However, given these relationships as well as polling on conspiratorial attitudes towards Covid-19 across party lines (for example, Figures 1.4 and 1.7) conspiracy theories about the pandemic certainly seem to lead to lower public health outcomes in the US as a whole and in Republican states specifically.

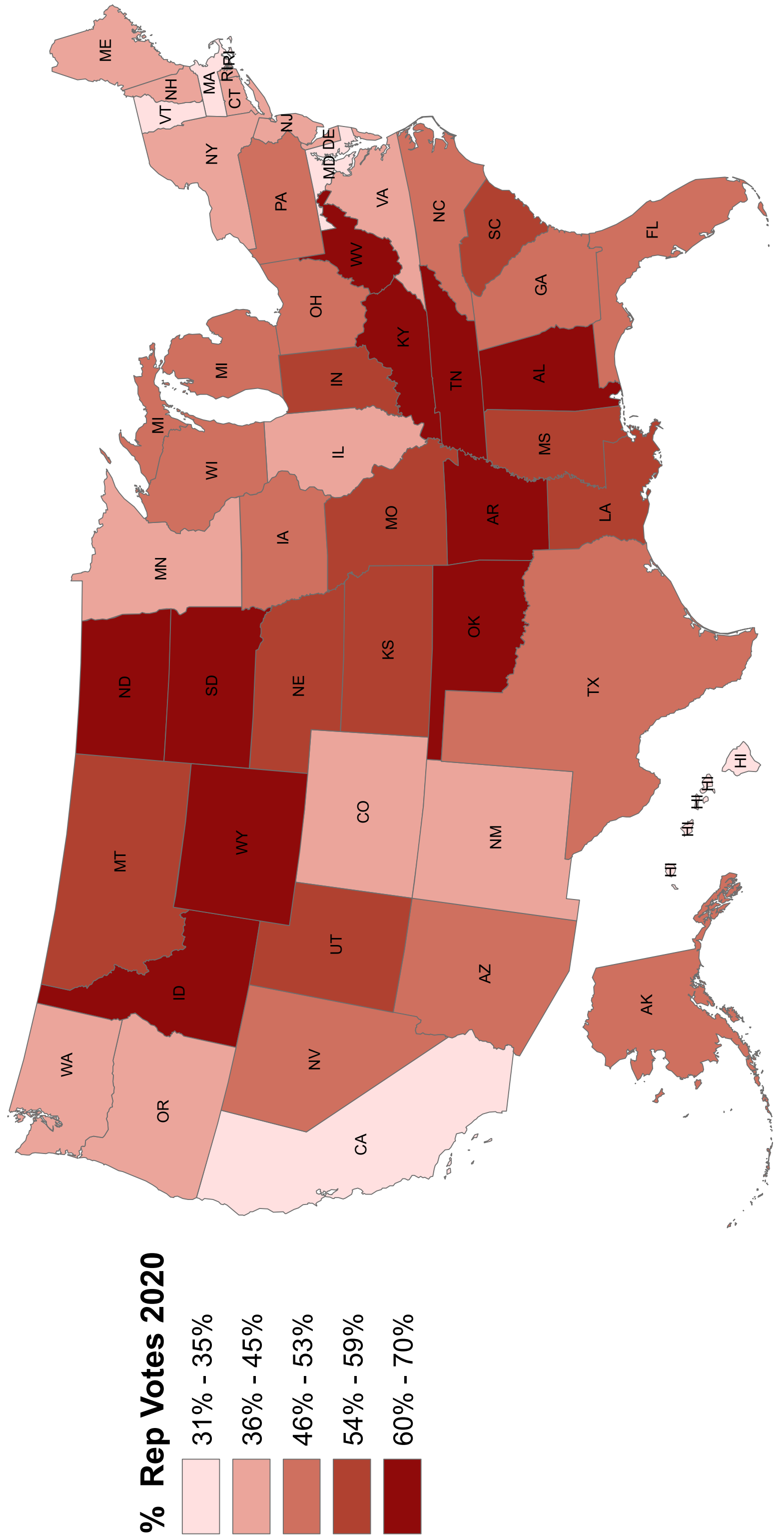
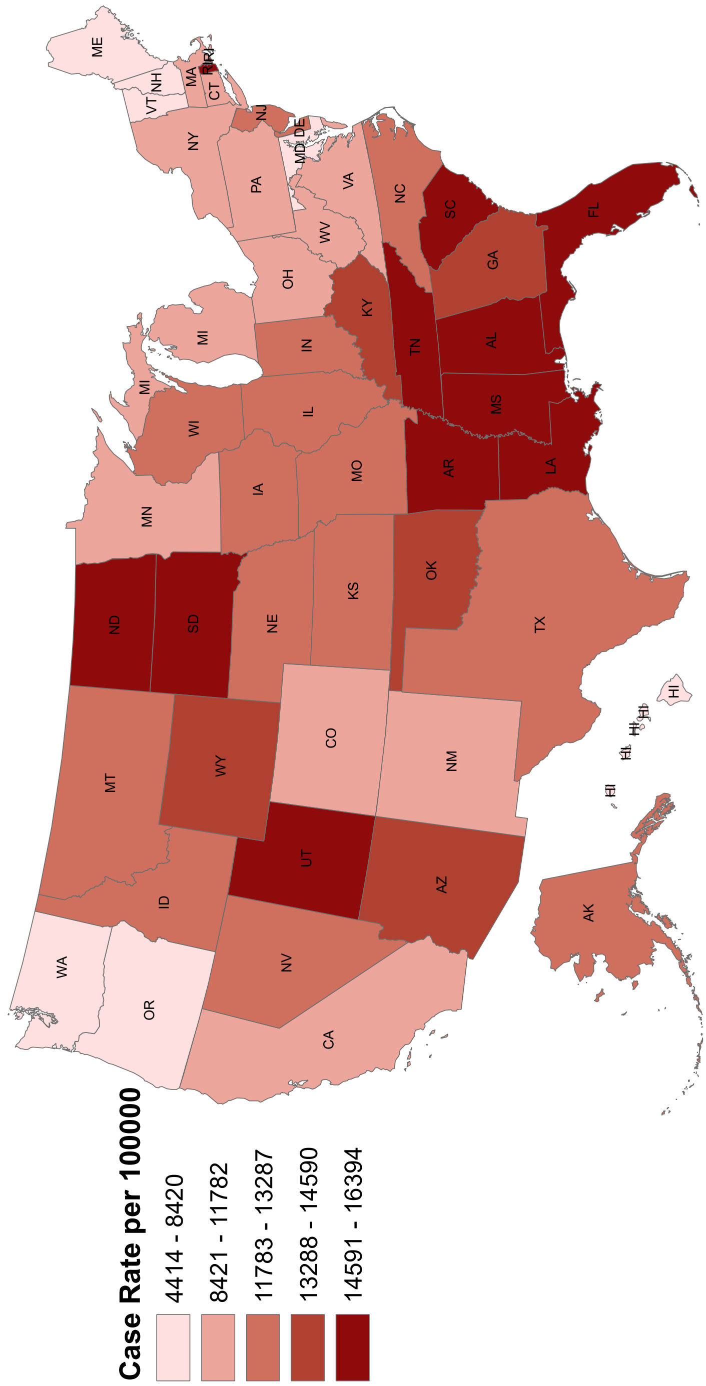


Figure 1.5: 2020 Presidential Election: Republican Vote by State

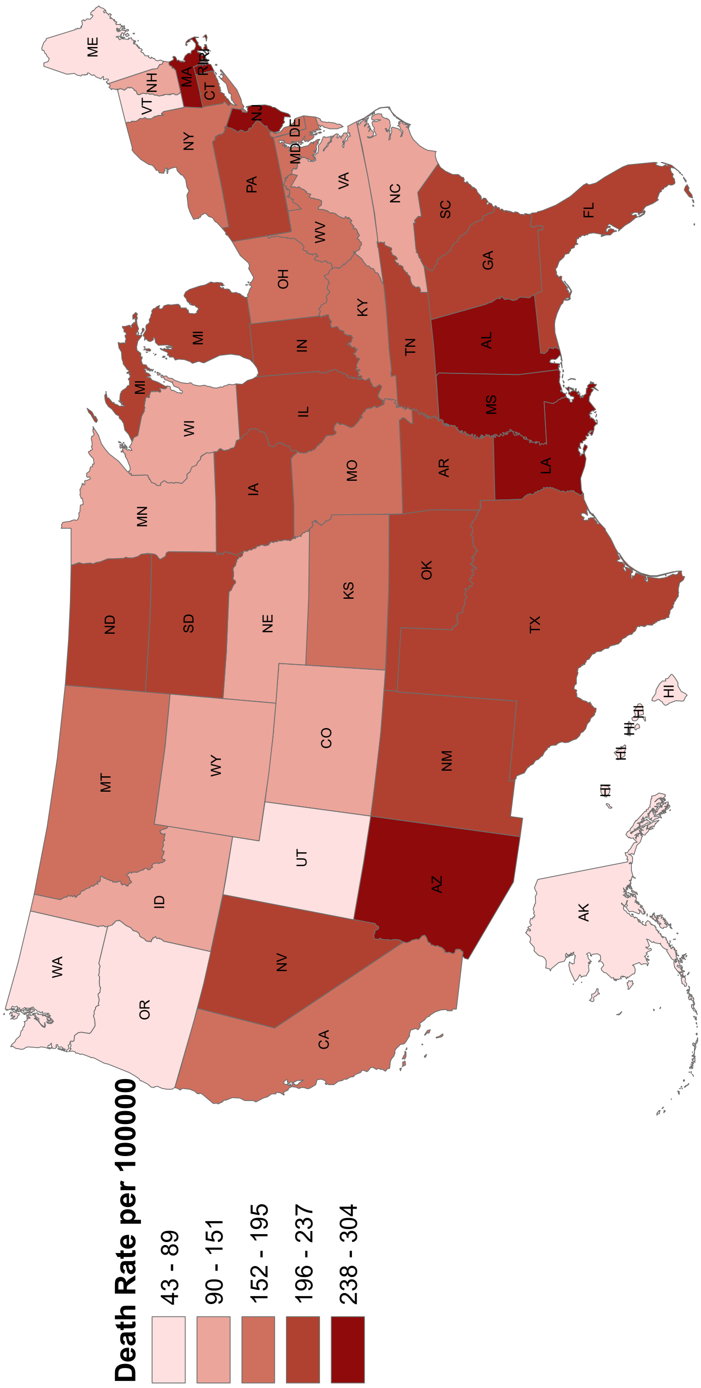
Source: The Cook Political Report (https://cookpolitical.com/2020-national-popular-vote-tracker)

Figure 1.6: Covid-19 Cases and Deaths by State



(a) Cases per 100,000

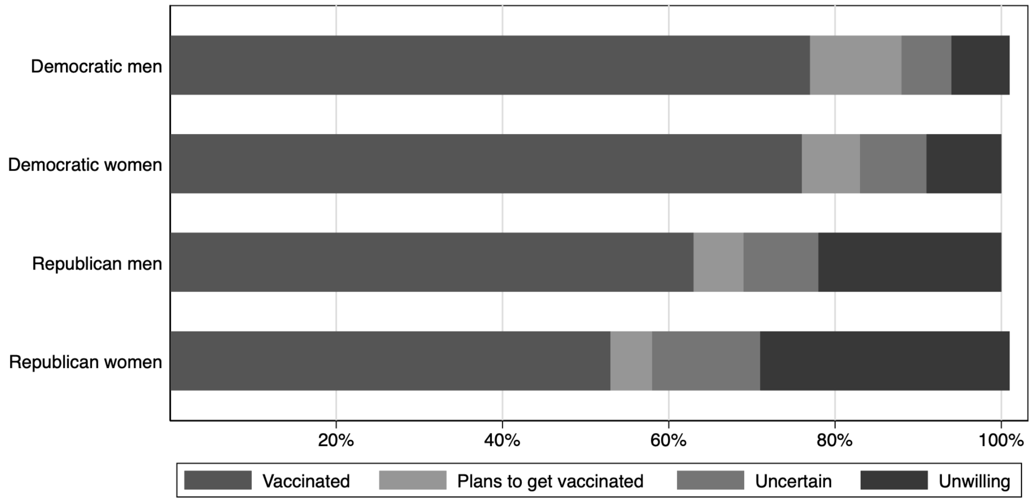
Figure 1.6: Covid-19 Cases and Deaths by State (continued)



(b) Deaths per 100,000

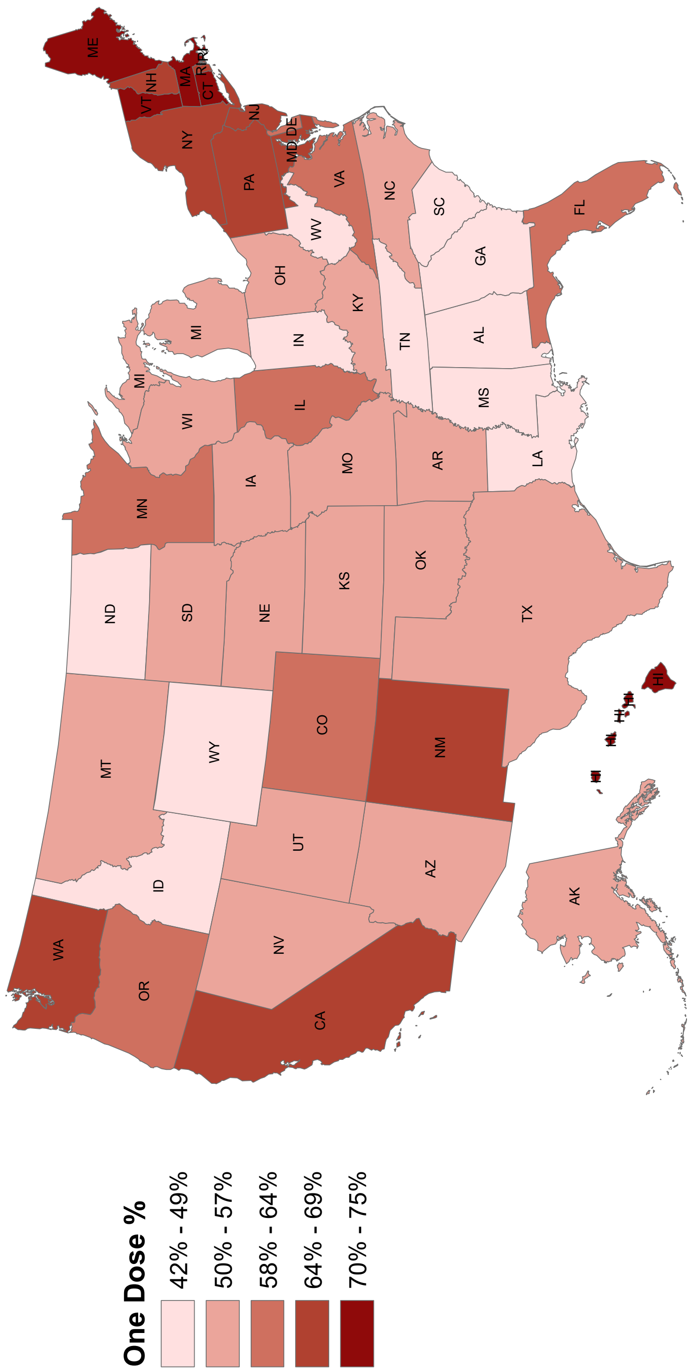
Source: Centers for Disease Control and Prevention (*https://covid.cdc.gov/covid-data-tracker*)

Figure 1.7: Vaccine Scepticism by Party and Gender



Source: Morning Consult (https://morningconsult.com/covid19-vaccine-dashboard/)

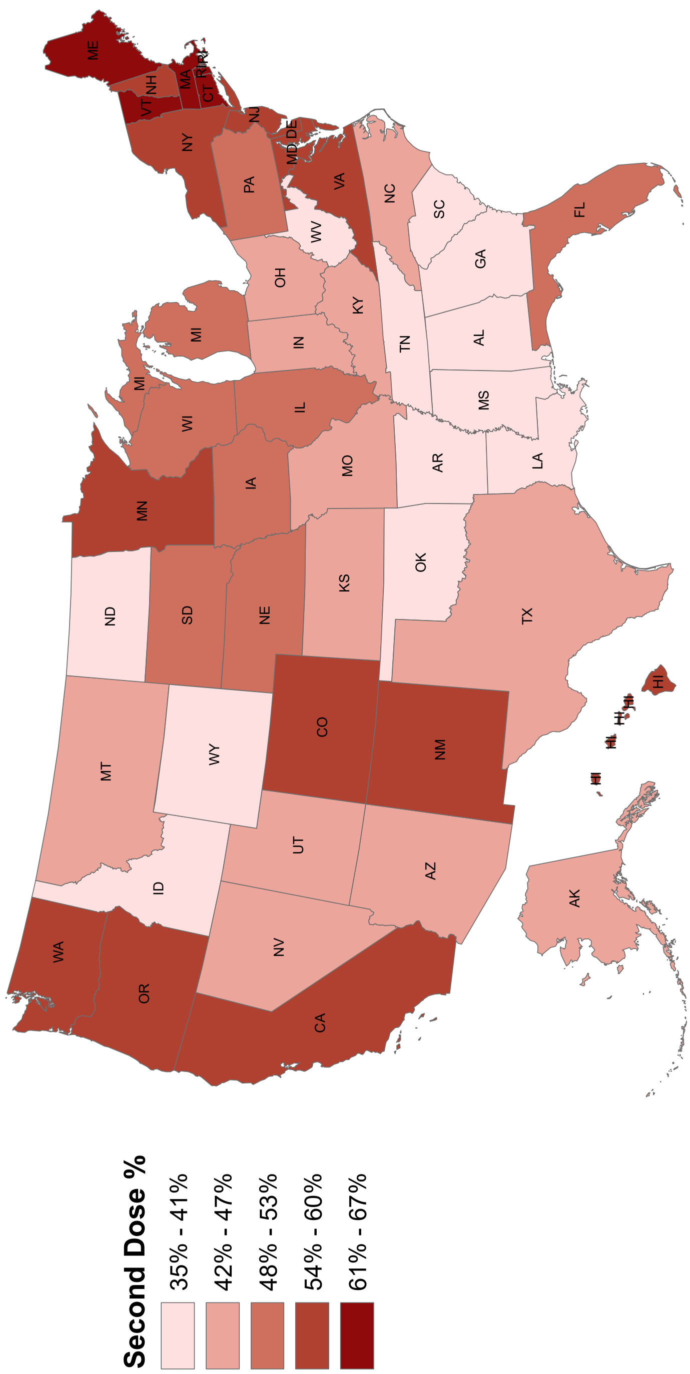
Conspiratorial beliefs continue to harm public health in the United States. Despite having a head start on most countries only 75.4 per cent of adults in the US have at least one vaccine dose. Anyone who can be vaccinated can avail of one so the approximately 25 per cent of adults who are completed unvaccinated either cannot be vaccinated for medical reasons (a very small proportion of those who or unvaccinated) or do not want to be vaccinated. As Figure 1.8 demonstrates certain Republican states have, on average, lower vaccine rates than their Democratic counterparts while Figure 1.7 shows that Republicans are more vaccine sceptic.



(a) First Dose

Figure 1.8: Vaccine Take Up by State

Figure 1.8: Vaccine Take Up by State (continued)



(b) Second Dose

Source: Mayo Clinic (*https://www.mayoclinic.org/coronavirus-covid-19/vaccine-tracker*)

For example, Alabama, Mississippi, and Wyoming, and have 35, 36, and 37 per cent respectively of the entire population vaccinated at the time of writing. By way of comparison, over 90 per cent of Ireland's adult population has been fully vaccinated against Covid-19 while 70.5 per cent of the entire population is fully vaccinated.[1] Polling suggests that the majority of those unvaccinated have no intention of receiving the dose and site a fear of side effects (despite overwhelming evidence that these are incredibly rare) and a lack of trust in government as their reasons for not receiving the vaccines (Newport 2021). Vaccination is the best defence against Covid-19 and as long as conspiracy theories surrounding both the virus and the vaccine continue to circulate, the United States public health will continue to be damaged (Murphy, Vallières, Bentall, Shevlin, McBride, Hartman, McKay, Bennett, Mason, Gibson-Miller et al. 2021).

1.8.3 Donald Trump, the 2020 Election, and Trust in Institutions, and Political Violence

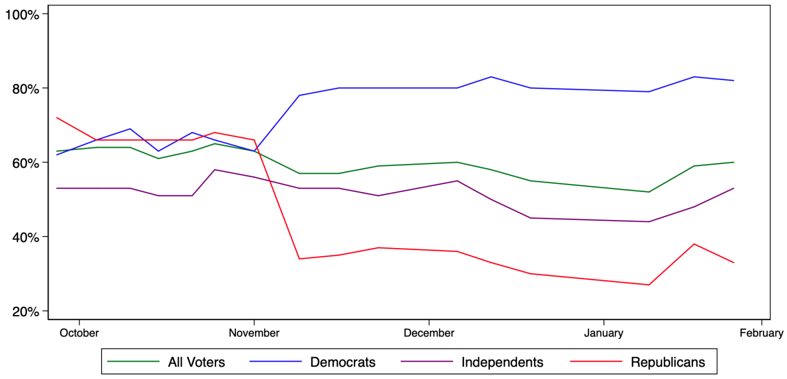
Conspiracy theories surrounding election fraud are not new in America. In 1960 claims surrounding vote counts in Illinois being rigged to give the state to John F Kennedy in the Presidential election were so widespread that it has since become conventional wisdom. Evidence does suggest that there were voting irregularities. However, these were not enough to give the state to JFK's opponent, Richard Nixon (Kallina 1985). However, Donald Trump went further than most in his use of conspiracy theories to undermine the legitimacy of his popular vote loss to Hilary Clinton in 2016 Electoral College and his loss to Joe Biden in 2020. In the build-up to the 2016 election, Trump warned of possible widespread fraud in the upcoming election. In the wake of his surprise win, Trump maintained this conspiracy theory, citing it as the reason he did not win the popular vote. Subsequently, Trump repeatedly warned of widespread

[1] Information acquired from the Irish government and available at: `https://covid-19.geohive.ie/pages/vaccinations`. This information was acquired on 15 September 2021.

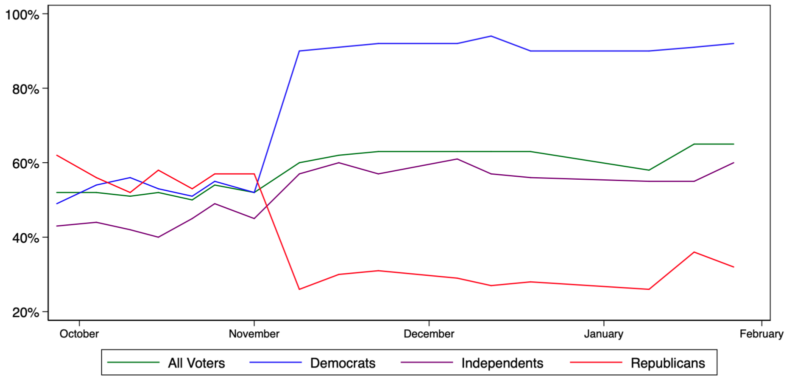
voter fraud in the build-up to the 2020 election. In the wake of his loss to Biden, Trump and his supporters cited several different conspiracy theories as to the reason he lost the election. These theories were widespread, varied, and ranged from electoral fraud through mail-in voting to ballot-box stuffing and dumping, dead people voting, and voting machines changing the vote preference. There was little to no evidence to support these theories with several court cases lodged by the Trump campaign being dismissed (Reuters 2021).

Despite this lack of evidence to support these conspiracy theories, a clear majority of Republicans believed that the election had not been free and fair. As Figure 1.9 outlines, post-election Republicans trust in the US election system fell from over 60 per cent to a low of approximately 30 per cent. A similar number believed that the election had not been free and fair. Of course, a dip is normal. In US politics those whose preferred candidate did not win often believe that the election had not been free and fair. However, as Figure 1.9(c) shows, this drop in trust was larger than what is usually observed for those on the losing side of an election with trust falling to an all time low. Further, 147 Republicans in Congress, motivated by the conspiracy theory, voted not to certify the election results (Yourish, Buchanan & Lu 2021). This vote was a move against democracy by elected officials. Therefore, Trump's rhetoric had genuinely undermined Republican's faith in democracy. This will potentially lower Republican engagement with the system in future. These conspiracy theories have also been used in states such as Georgia to bring in laws that make it more difficult to vote despite the lack of any evidence to suggest that there was widespread voter fraud in 2020 (Zurcher 2021).

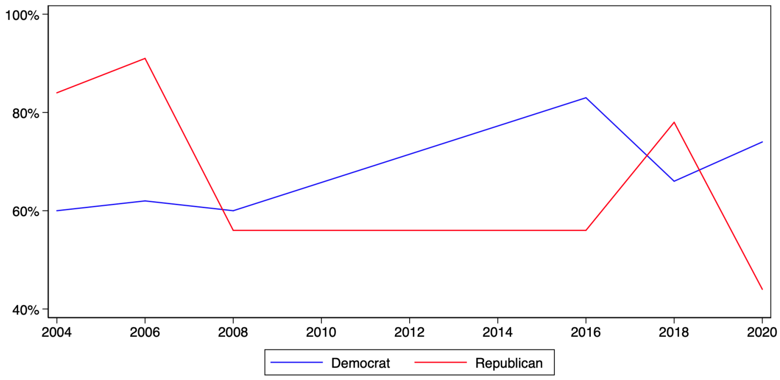
Figure 1.9: Trust in the US Election System by Party



(a) Trust in the US Election System (2020-21)



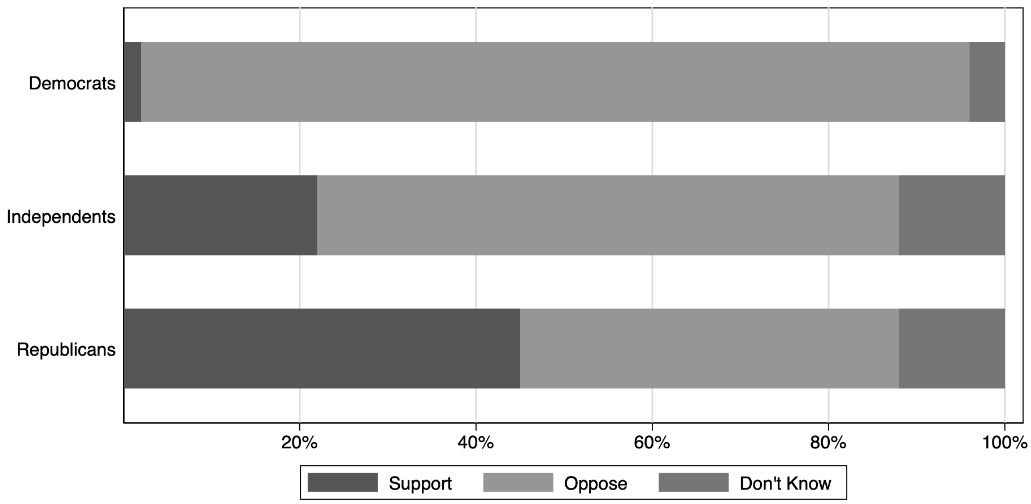
(b) Belief that the 2020 election was free and fair



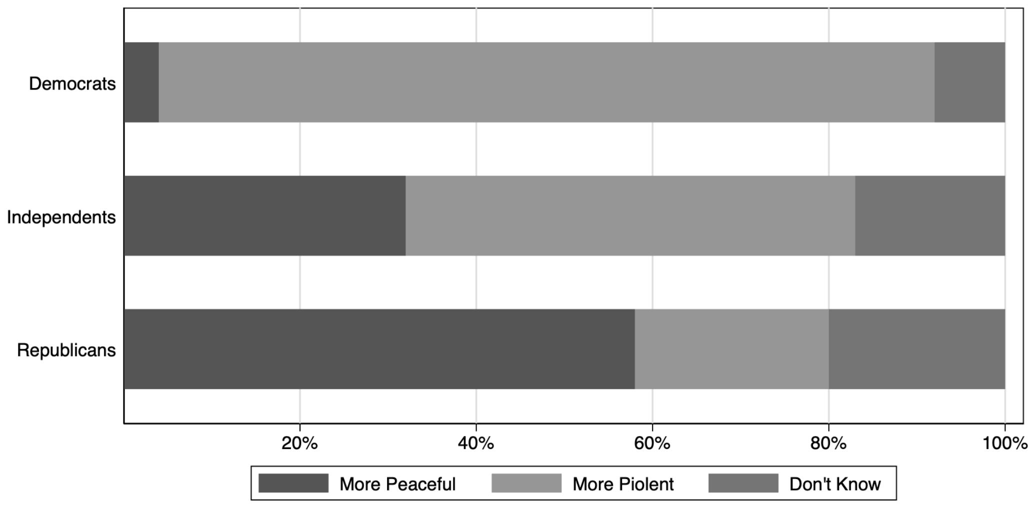
(c) Trust in the US Election System Over Time

Morning Consult (https://morningconsult.com/form/tracking-voter-trust-in-elections/) &
Gallup (https://news.gallup.com/poll/321665/confidence-accuracy-election-matches-record-low.aspx)

Figure 1.10: Views on the Capitol Insurrection



(a) Do you support the actions of those who stormed the Capitol?



(b) Do you think the protest was more peaceful or more violent?

Source: YouGov/Economist

(https://www.economist.com/graphic-detail/2021/01/07/nearly-half-of-republicans-support-the-invasion-of-the-us-capitol)

Damaging as the undermining of political institutions may be, the consequences of these conspiracy theories went even further. On 06 January 2021, the day Congress was to certify the Electoral College result, Trump supporters, motivated by election fraud conspiracy theories, stormed the US Capitol building in an attempt to stop the certification. Violence ensued with five people including police officers losing their lives (Tan, Shin & Rindler 2021). This was a clear example of a group of people, motivated by conspiracy theories trying to overthrow the democratic result of an election using violence. Further, as Figure 1.10 shows, a plurality of Republicans supported the actions of those who stormed the Capitol and despite the images of violence and the death toll were more likely to give the protestors the benefit of the doubt.

The Unique conspiratorial nature of 2020 and the inherent nature of America as a society mean that the United States in 2020 represents a good case study when investigating conspiracy theories.

1.9 Outline of the Thesis

This dissertation is divided into three quantitative chapters. Chapter 2 utilises a framing experiment to examine whether individuals are more likely to believe a conspiracy theory if they are exposed to the theory through a frame of either fear or anger. Chapter 3 uses Facebook posts, news articles, and news headlines to investigate if conspiratorial news outlets utilise heightened levels of fear and anger in their messaging. Chapter 4 studies the effect that the presence of fear and anger in Facebook posts has on the performance of conspiratorial outlets Facebook posts. Chapter 5 then discusses the importance, implications, and limitations of the findings presented in this dissertation.

Chapter 2

The Effect of Fear and Anger in Conspiratorial Messaging

Abstract

Why do some people believe in conspiracy theories while others do not? This chapter builds on recent literature examining the role that exposure to the theories plays in the development of conspiratorial beliefs. This chapter proposes that an important yet overlooked factor in influencing individuals perception of conspiracy theories is their exposure to these theories through negative emotive frames. Specifically, the chapter investigates the role of fear and anger in the formation of conspiracy beliefs. The literature holds that information cues are important drivers of conspiratorial beliefs. This chapter extends this, finding that these informational cues are stronger when given through a frame of either fear or anger. Using a framing experiment, this chapter helps in our understanding of the role that fear and anger play in the formation of individuals' conspiratorial beliefs. The findings presented here are mixed with results not statistically significant across all models. These mixed results highlight the important role that fear and anger play in the formation of conspiratorial beliefs.

2.1 Introduction and Motivation

Citizens rely on the news media for their information. Whether the information is economic, political, or social in nature. This relationship has changed somewhat in recent years with more and more people getting their information through social media. However, even in this context the news media still plays an important role. Especially when including non-traditional news media outlets. Such outlets have prospered with the advent of social media. Therefore, the news media still plays an important role in informing citizens (Jacob 2011). Conspiracy theories are no different. Fundamentally, just like any political information, people must be exposed to conspiratorial information in order to develop opinions on the conspiracy and its related events and thus the news media plays an important role here (Uscinski, Klofstad & Atkinson 2016).

The presence of emotionally charged language in conspiracy theories has been anecdotally noted in the literature. It is suggested that this language is used to engender a visceral and negative reaction to the information presented. Intuitively this makes sense. Conspiracy theories are, by their very nature, inherently negative. Conspiracies shine a negative light on important institutions. They seek to sew distrust. At the extreme, they seek to tear down the structures that govern society. It is hard to envisage such messages being delivered in a positive manner. Indeed, the process of believing in conspiracy theories is quite similar to opinion formation when in a heightened emotional state - fast, automatic and intuitive in nature. Further, negative emotions such as fear may elicit the existential motives underlying conspiratorial beliefs (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas et al. 2019). Despite this, the effect that negative emotion has on individuals' perceptions of conspiracy theories remains understudied.

This chapter investigates the role that the presence of fear and anger within conspiratorial messaging plays on individuals' perceptions of conspiracy theories. In doing so, the chapter contributes to the growing literature on the relationship between exposure to conspiracy theories and belief in said theories. Indeed, this chapter builds on Ucsinski, Klofstad, and Atkinson's (2016) seminal work on the effect of exposure on conspiratorial belief. Adding the extra strand of the interaction between exposure and fear and anger. While the literature is constantly learning more about the phenomenon that is conspiracy theories there remains empirical gaps. Belief in conspiracy theories has several negative consequences on society. Therefore, expanding knowledge on how people come to hold these beliefs is of the utmost importance.

This chapter presents an experimental study. The experimental study employs a crowd-sourced sample of 1,600 participants from Amazon's Mechanical Turk. Three treatment groups receive an almost identical news article. These articles discuss the existence of the Deep State in the United States. The only difference between the three articles is that certain words are altered in order to elicit different emotions (fear, anger, and neutral). A fourth group received a control article. This article discusses rainfall and crop yields and is entirely unrelated to the deep state conspiracy theory. Participants are randomly assigned to one of the fear, anger, neutral, and control groups. Through the employment of such a research design, this chapter can focus on the effect that exposure to a conspiracy theory through a negative emotive frame has on an individual's perception of that theory.

The results of this study indicate that participants exposed to the conspiratorial article through a frame of fear or anger are significantly more likely to believe in that theory than those exposed through a neutral frame and those in the control group. However, these results are not consistent across all models. The results are significant when controlling for confounding variables such as gender, age, ethnicity, education level, employment status, religiosity, scientific world-view, and several psychological factors. The validity of the manipulation is also in doubt. Thus, this study demonstrates the need for further enquiry into this puzzle.

2.1.1 Why people believe in conspiracy theories

Through survey data, political scientists know who is more likely to believe conspiracy theories and more specifically, who is more likely to believe particular theories. However, generally, conspiracy theories transcend gender, race, political ideology, and social class with all of these groups being susceptible to varying conspiracy theories (Brotherton 2015). For instance, African Americans are more likely to believe that crack cocaine was manufactured by the United States government to undermine their community (Pipes 1999). On the other hand, conservatives are more likely to think that Barack Obama was not born in the United States and, therefore, had no legitimate right to the presidency of the United States (Enders & Smallpage 2018). Further, the conspiracy theory that childhood vaccinations are linked to autism is subscribed to by both the far right and the far left in the United States (Brotherton 2015). Conservatives are more likely to believe that a powerful and secretive group known as the New World Order is conspiring to rule the world through an authoritarian government. However, there are people on the far left who also believe in this theory (Parsons et al. 1999, Briones et al. 2012, Uscinski & Parent 2014). Interestingly, evidence also suggests that in the United States those who support the party that holds the presidency are less likely to subscribe to conspiracy theories than those who support the opposition party. This is because wining groups feel less anxious and more in control and thus feel less of a need to explain the world through the prism of conspiracy theories (Bilewicz, Cichocka & Soral 2015).

From a social psychological point of view, there have been three motives behind belief in conspiracy theories identified by the literature. These are epistemic motives, existential motives, and social motives. Conspiracy theories allow people to explain complex events through simple narrative (epistemic motives), find a compensatory sense of safety and security when feeling threatened (existential motives), and allow one to feel good about the self and the in-group through the demonisation of the conspirator(s)(social motives) (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020).

There has been some attention paid to the role of emotion in the development of conspiracy beliefs. It has been observed that the process of believing in these theories is similar to the opinion formation process when in an emotional state and that negative emotions such as fear lead to some of the social-psychological motives underpinning conspiratorial beliefs (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). Despite these expectations, the investigation of the role emotion plays on conspiratorial beliefs remains limited.

2.1.2 The media, information exposure, and opinion formation

The scholarship on media effects has moved away from the traditional 'hypodermic needle' models - where the message is directly received and wholly accepted by the receiver - to instead focus on the subtle effects of information exposure. *Agenda setting* and *media priming* are similar insofar as the amount of attention the media pays to a particular political issue influences the level of importance that media consumers attach to that issue. Thus, the media subtly inform citizens which political topics they should care about, and by extension judge how political leaders or public policies are performing through the weight of attention that they give it (Kneafsey 2018).

Media framing focuses on the content of media stories rather than the regularity with which the media reports certain stories. The theory presented within the literature is that the context within which a news story is presented influences how the public interpret that particular issue (Kneafsey 2018). There is ample evidence to suggest that how a news story is presented to individuals influences how they perceive the news story (Kahneman & Tversky 1984, Iyengar 1994, Nelson, Clawson & Oxley 1997, McLeod & Detenber 1999, Druckman 2001*a*, De Vreese 2004, Scheufele & Tewksbury 2007, Gross 2008, Kühne et al. 2014, Lawlor 2015). Within the literature there is some debate as to the precise definition of framing. However, for this project the following definition will be utilized: *"Choices journalists make about how to cover a story-from the words, phrases, and images they convey to the broader 'angle' they take can result in substantially different portrayals of the very same event and the broader controversy it represents"* (Nelson, Clawson & Oxley 1997, Kneafsey 2018). To this end, framing stresses certain narratives in order to influence how individuals perceive certain issues. An oft-cited example is that of illegal immigration in the United States. Whether a media organization frames the debate using certain terms such as 'illegal' or 'undocumented' influences how the public perceives immigration policy (Merolla, Ramakrishnan & Haynes 2013).

The literature has identified the use of alternative frames as one of the primary mechanisms by which media organizations seek to influence public opinion (Kneafsey 2018) In this sense the media seeks to tell the public not just what issues they ought to think about but also how these issues should be thought about. News reports may focus on one particular aspect of an issue or report about an issue in a particular way. For instance, framing the issue of refugee flows as an economic burden for a state rather than the state's humanitarian obligation of a state has a significant effect on how individuals perceive refugees (Georgiou & Zaborowski 2017). Both frames confer different meanings to the issue and frame the debate. It is important to stress that this is not merely a theory. There is ample empirical evidence to suggest that media framing has a significant impact on public opinion. The scholarly work examining framing effects in the context has investigated issues like social welfare payments, social movements, free speech, public order, Turkey's application to the European Union, and trade unions. This is a wide range of policy issues, yet framing effects have been shown to have a significant impact across all of these areas (Nelson, Clawson & Oxley 1997, McLeod & Detenber 1999, Druckman 2001*a*, Slothuus 2007, de Vreese, Boomgaarden & Semetko 2011, Kneafsey 2018).

The media is perhaps the most important institution in the formation of public opinion. There is little doubt that, at times, the media often mirrors rather than manipulates public opinion. However, the causal process does not flow in one direction. There is ample evidence that through agenda setting, priming and framing the media exerts significant influence over the formation of public opinion. The media influences what political issues individuals think about and how they should think about them (DellaVigna & Kaplan 2007).

2.1.3 Emotion and opinion formation

Psychologists have long understood that emotion has a powerful impact on how humans perceive information (Strongman 1978). Across the three prominent political psychology theories of affect (attitude, appraisal, and affective intelligence), emotion plays an important role in how we interact with and understand the world. In particular, under the most advanced and multi-disciplinary theory, Affective Intelligence (AIT), emotional stimuli precede conscious awareness and can have a profound impact on how individuals perceive the world around them both in the political realm and without (Marcus et al. 2019). The impact on opinion formation varies across emotions. For instance, fear increasing information gathering and enables people to break away from their preconceptions whereas anger tends to disable our information seeking facilities and causes us to rely on our preconceptions. However, the literature is somewhat mixed. For instance, there is evidence that fear both increases (Wodak 2015) and decreases (Marcus 2021) support for far-right populist parties. The context and appropriateness of the emotion to the message seems to play a role. However, overall it seems that fear leads individuals to develop opinions due to the negative attitudes towards the alternative that it engenders. Fear of terrorism or pandemics can cause citizens to rally around the flag, increasing support for the government (**?**). Fear of the potential actions of a political candidate can boost support for their opponent (Ansolabehere & Iyengar 1995).

The evidence strongly suggests that the media has been acutely aware of this relationship for decades, with the news media environment and political reporting in particular overwhelmingly negative (Iyengar 1994). It has been further observed that conspiracy theories are oft theories through an overwhelmingly negative emotive frame (Sunstein & Vermeule 2009). In particular, fear and anger have been noted within conspiratorial messaging (Fong et al. 2021). Intuitively this makes sense as conspiracy theorists aim to undermine a particular group of people, processes, or institutions. This mechanism is particularly strong in this case as a heightened sense of anxiety or loss of control makes individuals more susceptible to conspiracy theory ideology. Thus, in this case, the use of negative emotion is an appropriate communication strategy (Sunstein & Vermeule 2009). Despite the ample evidence on the role that negative emotions such as fear and anger can play in opinion formation, as well as the acknowledged presence in conspiratorial messaging, the impact that these negative emotions have on individuals' perception of conspiracy theories has yet to be systematically investigated.

2.2 Conspiracy, exposure, and emotion - a new theoretical framework

This chapter contends that an important yet overlooked factor in individuals perception of conspiracy theories is their exposure to conspiratorial articles through a negative emotive frame. More specifically, their exposure to conspiratorial articles framed through fear and anger. The use of negative emotive language within conspiratorial messaging has been anecdotally observed in the literature but never systematically studied (Sunstein & Vermeule 2009). This relationship is particularly potent in the context of conspiracy theories with people who are experiencing anxiety or a loss of control more likely to believe in conspiracy theories (Douglas, Sutton & Cichocka 2017, Douglas, Cichocka & Sutton 2020).

The literature holds that conspiracy theories are likely to have emotional underpinnings. This is because belief in conspiracy theories seems to be associated with the fast, automatic, and intuitive System 1 processes of opinion formation (Douglas, Cichocka & Sutton 2020). These processes are highly similar to those observed in through the AIT lens (Marcus et al. 2019). Research also shows that negative emotions such as fear and anger may increase a person's susceptibility to conspiracy theories as they fit with the existential motives of conspiracy belief - that one is not in control or under threat. While these conspiracy theories do not assist in lowering one's emotive state, they do justify the feeling (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). Thus, belief in conspiracy theories is, at least theoretically, strongly rooted in negative affect (van Prooijen & Douglas 2018).

The use of negative emotions such as fear and anger also makes intuitive sense in the context of conspiracy theories. Conspiracy theorists are not trying to build something up or convince of its merits. They are trying to tear down or undermine existing institutions. With negative emotions that engender negative attitudes naturally make suiting this context (Whitson, Galinsky & Kay 2015, Klein, Clutton & Dunn 2019). For example, fear was the catalyst for the spread of McCarthyism and the 'Red Scare' in America (Fong et al. 2021). Anger, on the other hands, has been shown to increase engagement with conspiracy theories, influencing people's likelihood to believe in the theory and also influencing the spread of conspiracy theories (Mitra, Counts & Pennebaker 2016).

While individual-level traits such as net affect need for chaos, age gender, ethnicity, education, class, employment status, political engagement, ideology, and conspiratorial predisposition have all been studied in-depth, they are limited to telling us who is more likely to believe a conspiracy theory rather than why. And while recent scholarship has demonstrated that informational cues play an important role in the development of conspiratorial opinions. However, there is a dearth of research on the role that the framing of these conspiracy theories plays and more specifically the level of emotion within these frames.

Further to the role that emotion plays in the development of public opinion, media and communications scholars have overwhelmingly demonstrated the powerful influence that the media has on public opinion (Druckman 2001*a*, Herman & Chomsky 2010). The media has several mechanisms through which it, either by accident or by design, influences public opinion (McLeod & Detenber 1999, Slothuus 2007, de Vreese, Boomgaarden & Semetko 2011). Therefore, it is reasonable to believe that the media's reporting of conspiracy theories influences individuals' perceptions of these theories. Thus, an individual who consumes news media relating to conspiracy theories they are more likely to subscribe to those conspiracy theories, especially when this information is framed through negative emotive frames.

It is then unsurprising that conspiracy theorists might utilize negative emotions such as fear and anger in their messaging. These actors do not seek to advance positive messages; rather they seek to undermine political institutions, political opponents, and democratic values (Sunstein & Vermeule 2009). Given the impact that potential impact that emotion has on opinion formation and the fact that conspiracy theorists seek to engender negative opinions within their audience, the use of such language in their communication would be an appropriate tactic (Fong et al. 2021). This expectation is further compounded by the fact that when people access new information through a frame of negative emotions, they are more likely to spread this information (Oliver & Wood 2014). This further assists in propagating conspiracy theories.

Given the noted presence of negative emotive language in conspiracy theories, the nature of conspiracy theories, the impact that negative emotion has on opinion formation, and the theoretical fit between negative emotions like fear and anger and conspiratorial beliefs there is strong reason to suspect that exposure to a conspiracy theory through a negative emotive frame will increase the probability of an individual believing in that conspiracy theory.

To this end this research chapter proposes the following hypothesis:

Hypothesis 2.1 *An individual who is exposed to a conspiracy theory is more likely to believe that conspiracy theory than an individual who is not exposed to the same conspiracy theory.*

Hypothesis 2.2 *The effect of exposure to a conspiracy theory (Hypothesis 1) is more pronounced when the exposure is through an emotive frame.*

That is, individuals are more likely to believe the conspiracy theory if that theory has been presented to them with this effect heightened iin the presence of fear and anger.

2.3 Data and Methodology

To investigate Hypotheses 2.1 and 2.2 a framing experiment was fielded to 1,600 individuals living in the United States of America through Amazon's Mechanical Turk online crowdsourcing platform.[1] The experiment took place in October 2020. Respondents were randomly assigned to one of four groups, three treatment groups and one control group. The following section outlines the case selections, experimental design, ethical implications, and the empirical strategy of the chapter.

2.3.1 Case Selection

This chapter uses an article relating to the 'Deep State' conspiracy theory to test the two hypotheses. Originating in Turkey, the deep state is defined as a faceless clique that secretly holds power. This clique consists of high-level officials from the national intelligence service, military, academia, judiciary, and bureaucracy. The members of this clique are ultra-statist (Nefes 2018, p. 387). In an American context, they are dedicated to globalism. This deep state overlaps with many other conspiracy theories. Some hold that the deep state was responsible for the Kennedy assassination, worked against Donald Trump for the duration of his presidency, and allowed Hilary Clinton to not face prosecu-

[1]The survey design along with the theoretical argument was per-registered on the EGAP registry under the registration number 20200402AB.

tion over her mishandling of classified emails (Uscinski 2020, p. 6, 11).

The deep state conspiracy theory has been chosen as it transcends the right/left divide. According to a Monmouth University poll, 59 per cent of Democrats, 59 per cent of Republicans, and 62 per cent of Independents think that unelected or appointed government officials have too much influence in determining federal policy. While 74 per cent of voters believe that a group of unelected government and military officials secretly manipulate or direct national policy[2] Indeed, the deep state conspiracy theory is ideologically flexible. Predictably, to Trump supporters, the Muller investigation into collusion between the Trump campaign and the Russian government in 2016 was an example of the Deep State working against President Trump. While those who believed that Trump had conspired with the Russian government believed that the investigations eventual findings was yet another example of the deep state refusing to hold the powerful accountable for their actions, no matter how heinous the crimes committed (Uscinski 2018).

In previous research on individuals perceptions of conspiracy theories it has been noted that the use of partisanship plays an important role in which conspiracy theories an individual will believe (Miller, Saunders & Farhart 2016, Uscinski, Klofstad & Atkinson 2016, Hart & Graether 2018). It is of the utmost importance to minimise the impact that individuals' partisan identity has on results. Given that this conspiracy theory traditionally transcends ideology it is an appropriate theory to utilize for the framing experiment. This will allow for a greater understanding of the treatment effect. Thus, this conspiracy theory offers a favourable case upon which to test the hypothesis presented in this chapter.[3]

[2]This information was obtained from the Monmouth University press release (`https://www.monmouth.edu/polling-institute/documents/monmouthpoll_us_031918.pdf/`)

[3]It has to be noted that at the time the experiment was fielded then-President Donald

2.3.2 Experimental Design

In the experiment participants were randomly exposed to a news article relating to the deep state through varying emotive frames (namely fear, anger, and neutral) as well as a control article on an unrelated topic. Such a technique has been long used in the political communication in order to demonstrate how exposure to information influences public opinion (Druckman 2001*a*). However, in the specific context of the study of emotion and public opinion it is generally unused. Instead, researchers often rely on techniques such as priming emotions prior to informational exposure in order to evaluate how an emotional state impacts opinion formation (Brinson & Stohl 2012). Other studies have examined how an emotional world-view impacts public opinion (Marcus 2021). Some literature, uses observational data from the media environment and public opinion data to draw conclusions on the link between emotion and public opinion (Hu, Wang, Luo, Zhang, Huang, Yan, Liu, Ly, Kacker, She et al. 2021). To-date leaving most of the language largely unchanged while only manipulating certain words in order to elicit certain emotions has been largely unused. This study acknowledges that such a methodology is imperfect, especially in the context of the co-occurrence of certain emotions. However, this manipulation is an attempt to isolate how the words that are presented to individuals through the written media impact upon their opinion of the information presented. This method also aims, by keeping the methods as similar as possible, to to separate any effect caused by the treatment (i.e., the varying emotive frames) and the content of the story itself (Wirz 2018).

One other major concern about using framing experiments such as the one

Trump and several members of the Republican party and right-wing information sphere had been warning of the potential for widespread voter fraud in the upcoming 2020 Presidential Election. While not at the time directly linked to the deep state there is was certainly a cross-over between the two conspiracy theories.

proposed here is the difficulty of generalization to non-laboratory settings. To address these issues and in doing so, enhance the external validity of this field experiment, the stimuli must be presented in a realistic setting so that they appear genuine (Druckman 2001*b*). Ideally, a researcher would be able to use real news stories as the frame. This would avoid constructed frames and their associated issues (Plaisance & Deppa 2009). However, in this particular experiment, it was impossible due to the aforementioned difficulty in separating the effect of the emotion and the effect of the quality of writing. Thus, this project constructed frames. To address this concern, the article is presented to look like an article downloaded directly from LexisNexis. This is done to create a setting that resembled what the individual may realistically be exposed to. The three treatment articles and one control article are available in Appendix A.1.

After reading their randomly assigned article all respondents are asked on a 7-point Likert scale, *"To what extent do you agree with the following statement: 'A shadow government, known as the 'Deep State' controls American society'?"* The respondents were also asked how the article made them feel. This is done to evaluate whether or not the frames are indeed eliciting the intended emotional responses. Respondents also answered a series of comprehension questions about the content of the article. This is done to ensure participants read the articles in their entirety and did not simply select random answers to finish the questionnaire as quickly as possible.

Individual-level demographic characteristics influence individuals perceptions of different conspiracy theories. Therefore, participants were asked their age, gender, citizenship status, ethnicity, employment status, education level, religiosity, scientific worldview, and party registration. These factors potentially influence how individuals perceive conspiracy theories and are therefore included (Brotherton 2015). Further to these demographic characteristics, certain individual-level personality traits have the potential to influence perceptions of conspiracy theories and also how individuals respond to emotive queues. Namely, an individual's need for chaos and their willingness to engage in political protest and violence (van Prooijen & Acker 2015, Hart & Graether 2018). Thus, a measurement of both has been included. Additionally, a measurement of the individuals Positive and Negative Affect Schedule (PANAS) is also included. PANAS measures an individual's feelings and emotions (Watson, Clark & Tellegen 1988). An individuals' feelings and emotions can influence how the participant responds to new information (Magyar-Moe 2009). This relationship is heightened in the presence of emotive frames (Lecheler, Bos & Vliegenthart 2015). Importantly, PANAS is measured before the respondents receive their randomly allocated article. This is done to avoid the negative emotion within the frames impacting the individual's mood. These measurements as well as all questions asked in the framing experiment can be seen. A flow chart of the experiment is provided in Appendix A.2.

2.3.3 Sampling Procedure

Launched in 2005 as a crowdsourcing marketplace, Amazon's Mechanical Turk (MTurk) allows 'requesters' to post-human intelligence tasks (HITs) to be completed by 'Turkers' for a set, usually small fee. Since its launch, there has been an exponential growth in social science research conducted on the platform (Buhrmester, Talaifar & Gosling 2018). This is likely because MTurk has been identified as an efficient method for collecting inexpensive high-quality data (Stewart, Ungemach, Harris, Bartels, Newell, Paolacci, Chandler et al. 2015). Indeed, evidence suggests that this data is equivalent or superior in quality to that collected in laboratory settings, from professional online panels, and using market research companies. This holds across a variety of research designs and types of data (Chmielewski & Kucker 2020). MTurk samples are also more representative than the oft used student samples in the literature (Goodman, Cryder & Cheema 2013). Furthermore, cost incentives (the fee paid by 'Requesters' to 'Turkers') do not appear to influence quality data (Buhrmester, Kwang & Gosling 2011).

This framing experiment was made available to any Turker who met a small set of eligibility requirements.[4] Therefore, the sample is not nationally representative. As this is a randomised control trial where participants are randomly assigned to a treatment or control group this is not seen as an issue (van Hoeven, Janssen, Roes & Koffijberg 2015). The racial makeup of the sample, as shown in Table 2.1, is not the same as the population as a whole. However, the divergence is not large. The sample is 77 per cent White while the US population as a whole is 76.3 per cent White. Black and African Americans make up 13.4 per cent of the American population but only 9 per cent of the sample. 7 per cent of the sample is Asian while only 5.9 per cent of the population is Asian. The biggest discrepancy comes from the Hispanic demographic. 18.5 per cent of the US population is Hispanic but only 5 per cent of the sample is Hispanic. However, many White Hispanics consider themselves White. Therefore, this discrepancy is probably not as large as it seems.[5] There are slightly more women than men (54 per cent versus 45 per cent). The sample is overwhelmingly educated (90 per cent have at least some college) and liberal (45 per cent registered Democrats as opposed to 27 per cent registered Republicans). This is to be expected as MTurk samples tend to be young, educated, and liberal. Research has shown this to not impact data quality. The full descriptive statistics are presented in Table 2.1.

[4]Participants had to be located in the United States, have a HIT approval rate (%) for all Requester's HITs greater than 95 per cent and have at least 5,000 HITs approved. The second two requirements are commonly used to obtain workers who return high-quality data.

[5]Figures obtained from the US Census website (https://www.census.gov/quickfacts/fact/table/US/PST045219).

2.3.4 Ethical Implications

This chapter studies the extent to which negative emotive frames increase individuals' propensity to believe in conspiracy theories. Belief in conspiracy theories can have a profoundly negative impact on society. Yet, to capture this mechanism participants had to be exposed to a conspiracy theory through a negative emotive frame. If participants kept any views engendered by the frames beyond this experiment there would be significant ethical implications given the relationship between these beliefs and lower political participation, increased political violence, and lower reception to scientific evidence. Therefore, at the end of the experiment, all participants were fully briefed as to the purpose of the experiment. Within this brief, they were informed that the article they had read was false. In doing so, the lasting effect of the frame was minimised.[6]

[6]This experiment received ethical approval from the Faculty of Arts, Humanities, and Social Sciences, Trinity College Dublin Ethics Committee on 09 March 2020.

Table 2.1: Sample Summary Statistics

Characteristics	Control Group	Neutral Group	Fear Group	Anger Group	Total
Age					
18 - 24	18 (4%)	11 (3%)	12 (3%)	10 (3%)	51 (3%)
25 - 34	110 (26%)	116(28%)	98(26%)	122(32%)	446 (28%)
35 - 44	121 (29%)	110 (27%)	118 (31%)	111 (29%)	460 (29%)
45 - 54	89 (21%)	81 (19%)	65 (17%)	70 (18%)	305 (19%)
55 - 64	52 (13%)	54 (13%)	62 (16%)	56 (15%)	224 (14%)
65 - 74	24 (6%)	36 (9%)	22 (6%)	14 (4%)	96 (6%)
75+	2 (%)	3 (%)	5 (1%)	3 (1%)	13 (1%)
Gender					
Male	190 (46%)	181 (44%)	171 (45%)	169 (44%)	711 (54%)
Female	222 (53%)	225 (55%)	202 (53%)	213 (55%)	862 (45%)
Other	0 (0%)	2 (%)	4 (1%)	2 (1%)	8 (1%)
Prefer not to say	4 (1%)	3 (1%)	4 (1%)	2 (1%)	14 (1%)
Race					
White	321 (77%)	325 (79%)	300 (79%)	288 (75%)	1,234 (77%)
Black or African American	33 (8%)	38 (9%)	37 (10%)	31 (8%)	139 (9%)
Hispanic	27 (7%)	18 (4%)	12 (3%)	18 (5%)	75 (5%)
Asian	28 (7%)	20 (5%)	26 (7%)	35 (9%)	109 (7%)
American Indian or Alaskan Native	0 (0%)	5 (1%)	(1%)	7 (2%)	16 (1%)
Native Hawaiian or Pacific Islander	1 (1%)	0 (0%)	0 (0%)	0 (0%)	1 (1%)
Other					21 (1%)
American Citizenship					
Is an American Citizen	412 (99%)	405 (98%)	378 (99%)	384 (99%)	1,579 (99%)
Is not an American Citizen	4 (1%)	6 (2%)	4 (1%)	2 (1%)	155 (1%)
Employment Status					
Employed Full-Time	272 (65%)	278 (68%)	251 (66%)	252 (65%)	1,053 (66%)
Employed Part-Time	48 (12%)	59 (14%)	56 (15%)	62 (16%)	225 (14%)
Unemployed Looking For Work	33 (8%)	24 (6%)	19 (5%)	28 (7%)	104 (7%)
Unemployed Not Looking For Work	23 (6%)	19 (5%)	24 (6%)	12 (3%)	78 (5%)
Retired	20 (5%)	22 (5%)	19 (5%)	28 (7%)	83 (5%)
Student	9 (2%)	2 (1%)	3 (1%)	2 (1%)	16 (1%)
Disabled	11 (3%)	7 (2%)	10 (3%)	8 (2%)	36 (2%)
Highest Level of Education					
Less than High School	4 (1%)	2 (1%)	0 (0%)	3 (1%)	9 (1%)
High School Graduate	36 (9%)	44 (11%)	41 (11%)	36 (9%)	157 (10%)
Some College	73 (18%)	74 (18%)	74 (19%)	68 (18%)	289 (18%)
2 Year Degree	43 (10%)	50 (12%)	53 (14%)	38 (10%)	184 (12%)
4 Year Degree	176 (42%)	154 (37%)	144 (38%)	171 (44%)	645 (40%)
Master's Degree or Equivalent	58 (14%)	67 (16%)	55 (14%)	54 (14%)	234 (15%)
Professional Degree	15 (4%)	10 (2%)	11 (3%)	11 (3%)	47 (3%)
Doctorate	11 (3%)	9 (2%)	4 (1%)	5 (1%)	29 (2%)
Political Interest					
Extremely Interested	80 (19%)	77 (19%)	78 (20%)	69 (18%)	304 (19%)
Very Interested	117 (28%)	123 (30%)	117 (31%)	110 (28%)	497 (29%)
Moderately Interested	116 (28%)	127 (31%)	107 (28%)	113 (29%)	463 (29%)
Slightly Interested	36 (9%)	26 (6%)	22 (6%)	30 (8%)	114 (7%)
Not Interested at All	67 (16%)	58 415%)	58 (15%)	64 (17%)	247 (15%)
Party Registration					
The Democratic Party	189 (45%)	183 (45%)	159 (42%)	158 (%)	689 (43%)
The Republican Party	89 (21%)	82 (20%)	61 (16%)	778 (%)	434 (27%)
The Green Party	2 (1%)	2 (1%)	6 (2%)	2 (1%)	12 (2%)
The Libertarian Party	6 (1%)	10 (2%)	7 (2%)	6 (2%)	29 (2%)
Other	32 (8%)	23 (%)	31 (8%)	34 (9%)	120 (8%)
No Registration	89 (21%)	82 (20%)	61 (16%)	78 (%)	310 (19%)

2.3.5 Empirical Strategy

Uscinski, Klofstad, and Atkinson (2016) hold that the following equation estimates the probability of an individual believing in a conspiracy theory:

$$BeliefinCT_i = \beta_0 + \beta_1 Exposure_i + \beta_2 PreDisposition_i + \beta_3 Partisanship_i + \epsilon_i$$

This chapter holds that an important, yet overlooked, factor is the emotive frame through which an individual is exposed to the conspiracy theory. Therefore, the following equation estimates the probability of an individual believing in a conspiracy theory:

$$BeliefinCT_i = \beta_0 + \beta_1 EmotiveExposure_i + \beta_2 PreDisposition_i + \beta_3 Partisanship_i + \epsilon_i$$

Unfortunately, the measurement of predisposition is only possible in a pre-experiment questionnaire. The limitations on MTurk and the finances available to the author meant that this was not possible. The question regarding predisposition to conspiracy theories was included in the questionnaire following exposure. However, the measurement almost certainly suffers from post-treatment bias. Indeed, the measurement has an approximate 0.70 correlation with belief in the deep state. Further, the predisposition is statistically significantly higher for those exposed to a treatment group vis-a-vis the control group. Therefore, this measurement cannot be included.

Hypothesis 1

This chapter concurs with Uscinski, Klofstad, and Atkinson (2016) that exposure to a conspiracy theory makes it more likely that an individual believes in that conspiracy theory. Therefore, this chapter presents the following equation to estimate the probability of an individual believing in a conspiracy theory:

(1) $Y_i = \beta_0 + \beta_1 Exposure + \epsilon_i$

Two further models are also offered. These incorporate various control variables that have been outlined by the literature and discussed in the empirical design subsection of this chapter. There are two additional models because some measurements contain multiple questions and have been combined into single measurements through both principal component analysis and factor analysis. Model 2 contains the principal component analysis measurements and Model 3 contains those with factor analysis. These equations are as follows:

(2) $Y_i = \beta_0 + \beta_1 Exposure + \beta_4 Gender + \beta_5 Age + \beta_6 Race + \beta_7 EmploymentStatus + \beta_8 Education + \beta_9 Religiosity + \beta_{10} ScientificWorldview + \beta_{11} Republican + \beta_{12} ARISradical_{principal} + \beta_{13} ARISnonradical_{principal} + \beta_{14} PANASpsoitive_{principal} + \beta_{15} PANASNegative_{principal} + \beta_{16} NeedforChaos_{principal} + \epsilon_i$

(3) $Y_i = \beta_0 + \beta_1 Exposure + \beta_4 Gender + \beta_5 Age + \beta_6 Race + \beta_7 EmploymentStatus + \beta_8 Education + \beta_9 Religiosity + \beta_{10} ScientificWorldview + \beta_{11} Republican + \beta_{12} ARISradical_{factor} + \beta_{13} ARISnonradical_{factor} + \beta_{14} PANASpsoitive_{factor} + \beta_{16} NeedforChaos_{factor} + \epsilon_i$

Hypothesis 2

This chapter also expands on Uscinski, Klofstad, and Atkinson (2016). stating that exposure to a conspiracy theory through a negative emotive frame makes it more likely that an individual believes in that conspiracy theory than exposure alone. Therefore, this chapter presents the following equations to estimate the probability of an individual believing in a conspiracy theory:

(4) $Y_i = \beta_0 + \beta_1 NegativeEmotiveExposure + \beta_2 Control + \epsilon_i$

(5) $Y_i = \beta_0 + \beta_1 NegativeEmotiveExposure + \beta_2 Control + \beta_3 Gender + \beta_4 Age + \beta_5 Race + \beta_6 EmploymentStatus + \beta_7 Education + \beta_8 Religiosity + \beta_9 ScientificWorldview + \beta_{10} Republican + \beta_{111} ARISradical_{principal} + \beta_{12} ARISnonradical_{principal} + \beta_{13} PANASpsoitive_{principal} + \beta_{14} PANASNegative_{principal} + \beta_{15} NeedforChaos_{principal} + \epsilon_i$

(6) $Y_i = \beta_0 + \beta_1 NegativeEmotiveExposure + \beta_2 Control + \beta_3 Gender + \beta_4 Age + \beta_5 Race + \beta_6 EmploymentStatus + \beta_7 Education + \beta_8 Religiosity + \beta_9 ScientificWorldview + \beta_{10} Republican + \beta_{11} ARISradical_{factor} + \beta_{12} ARISnonradical_{factor} + \beta_{13} PANASpsoitive_{factor} + \beta_{14} PANASNegative_{factor} + \beta_{15} NeedforChaos_{factor} + \epsilon_i$

(7) $Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + \beta_3 Control + \epsilon_i$

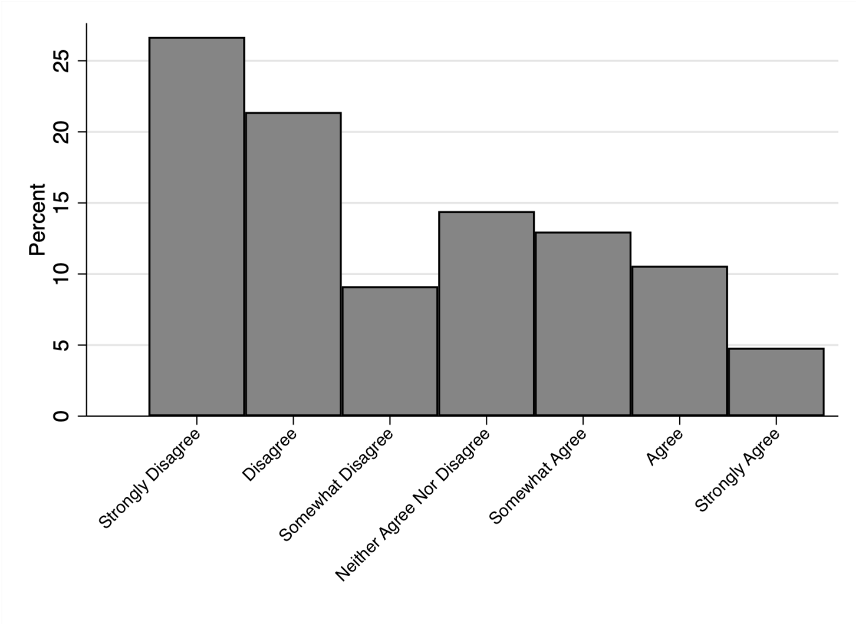
(8) $Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + \beta_3 Control + \beta_4 Gender + \beta_5 Age + \beta_6 Race + \beta_7 EmploymentStatus + \beta_8 Education + \beta_9 Religiosity + \beta_{10} ScientificWorldview + \beta_{11} Republican + \beta_{12} ARISradical_{principal} + \beta_{13} ARISnonradical_{principal} + \beta_{14} PANASpsoitive_{principal} + \beta_{15} PANASNegative_{principal} + \beta_{16} NeedforChaos_{principal} + \epsilon_i$

(9) $Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + \beta_3 Control + \beta_4 Gender + \beta_5 Age + \beta_6 Race + \beta_7 EmploymentStatus + \beta_8 Education + \beta_9 Religiosity + \beta_{10} ScientificWorldview + \beta_{11} Republican + \beta_{12} ARISradical_{factor} + \beta_{13} ARISnonradical_{factor} + \beta_{14} PANASpsoitive_{factor} + \beta_{15} PANASNegative_{factor} + \beta_{16} NeedforChaos_{factor} + \epsilon_i$

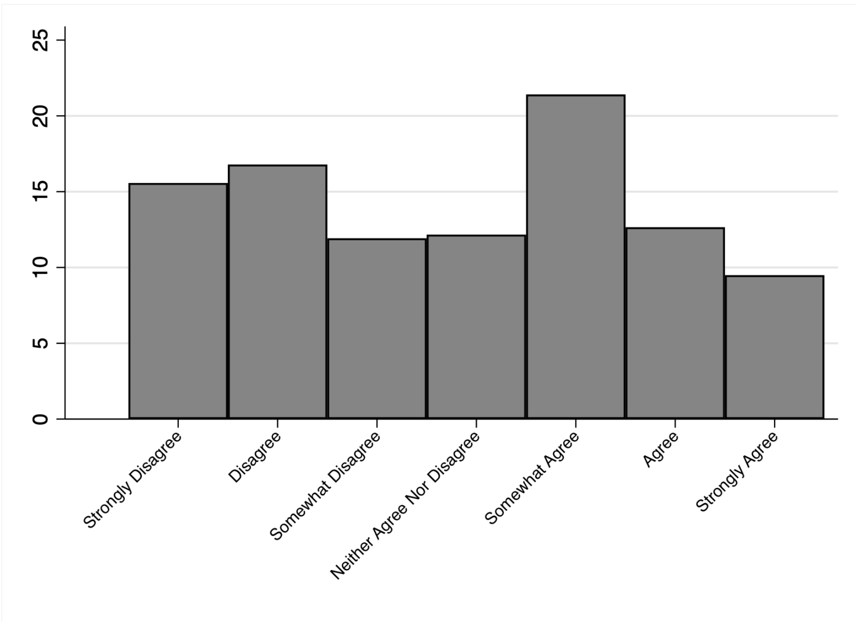
2.4 Results

Figure 2.1 outlines the distribution of belief in the 'Deep State' across the four groups. The control group is far less likely to believe in the conspiracy theory than those in the treatment groups. Further, those who received the conspiracy theory through a frame of fear or anger are more likely to believe the theory than those who received the theory in a neutral frame. Indeed, when grouping those who answered somewhat agree, agree, and strongly agree together, just over half of those in the fear treatment group stated that they agreed that "a shadow government, known as the 'Deep State' controls American society." For those in the anger treatment group, this figure is 49 per cent. In contrast, 44 per cent of those in the neutral treatment group agreed with the statement while only 28 per cent in the control group agreed. This section demonstrates that these differences are statistically significant.

Figure 2.1: Level of Agreement: “A shadow government, known as the ‘Deep State’ controls American society”

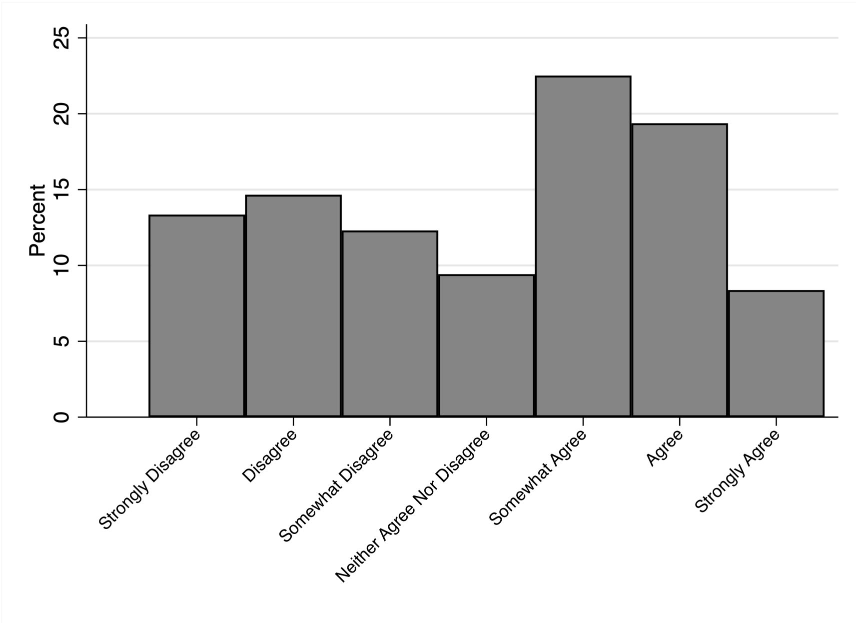


(a) Control Group

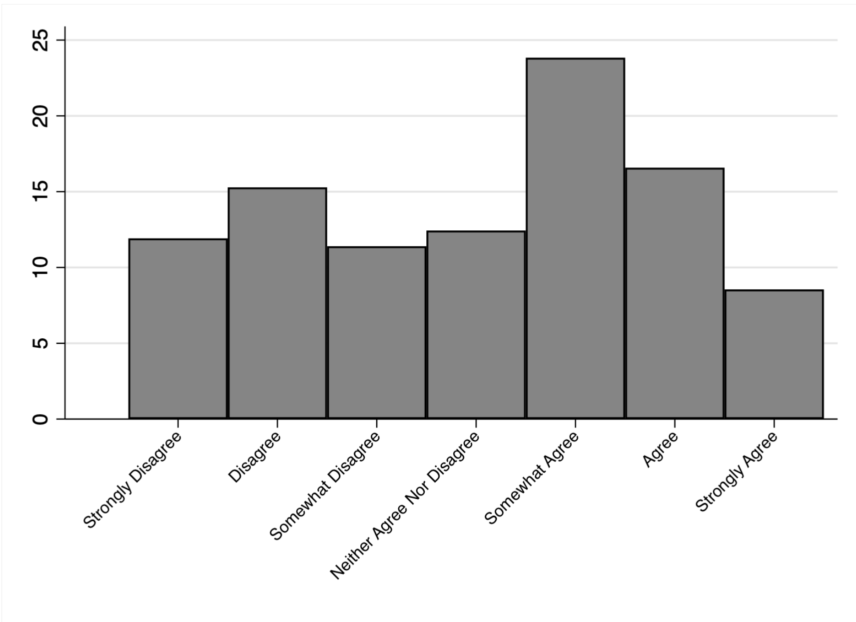


(b) Neutral Group

Figure 2.1: Level of Agreement: “A shadow government, known as the ‘Deep State’ controls American society” (continued)



(c) Fear Group



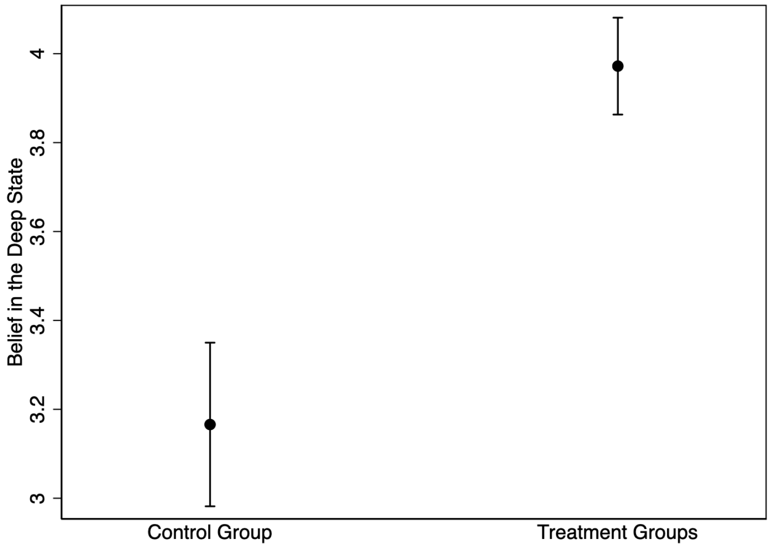
(d) Anger Group

2.4.1 Hypothesis 1

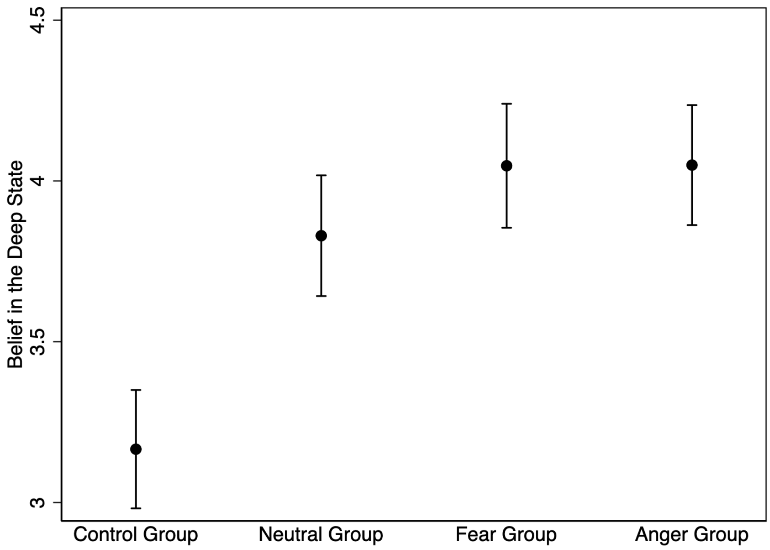
Figure 2.2 shows the participants who were exposed to the conspiracy theory (M = 3.97, SD = 1.91) compared to the control group (M = 3.17, SD = 1.91) demonstrated significantly higher belief in the deep state conspiracy, t(1593) = -7.4087, p = .0000. This relationship holds when the means of each treatment group are individually compared to the control group. This demonstrates that those exposed to the conspiracy theory significantly increases the likelihood of believing in the theory.

Table 2.2 shows that when using an ordinary least squares (OLS) regression this relationship holds. These results corroborate the argument that exposure to the Deep State conspiracy theory makes an individual significantly more likely to believe in the theory. As Models 2 and 3 in Table 2.2 and Figure 2.3 demonstrate, this relationship holds in the presence of confounding variables. This finding is unsurprising given previous evidence on both informational cues and conspiratorial belief as well as the wider literature on framing and media effects. They do, however, demonstrate the the frames are indeed having an effect. The full regression results are available in Appendix A.5.

Figure 2.2: Deep State Belief - Mean Response



(a) Control and Exposure Groups



(b) All Groups

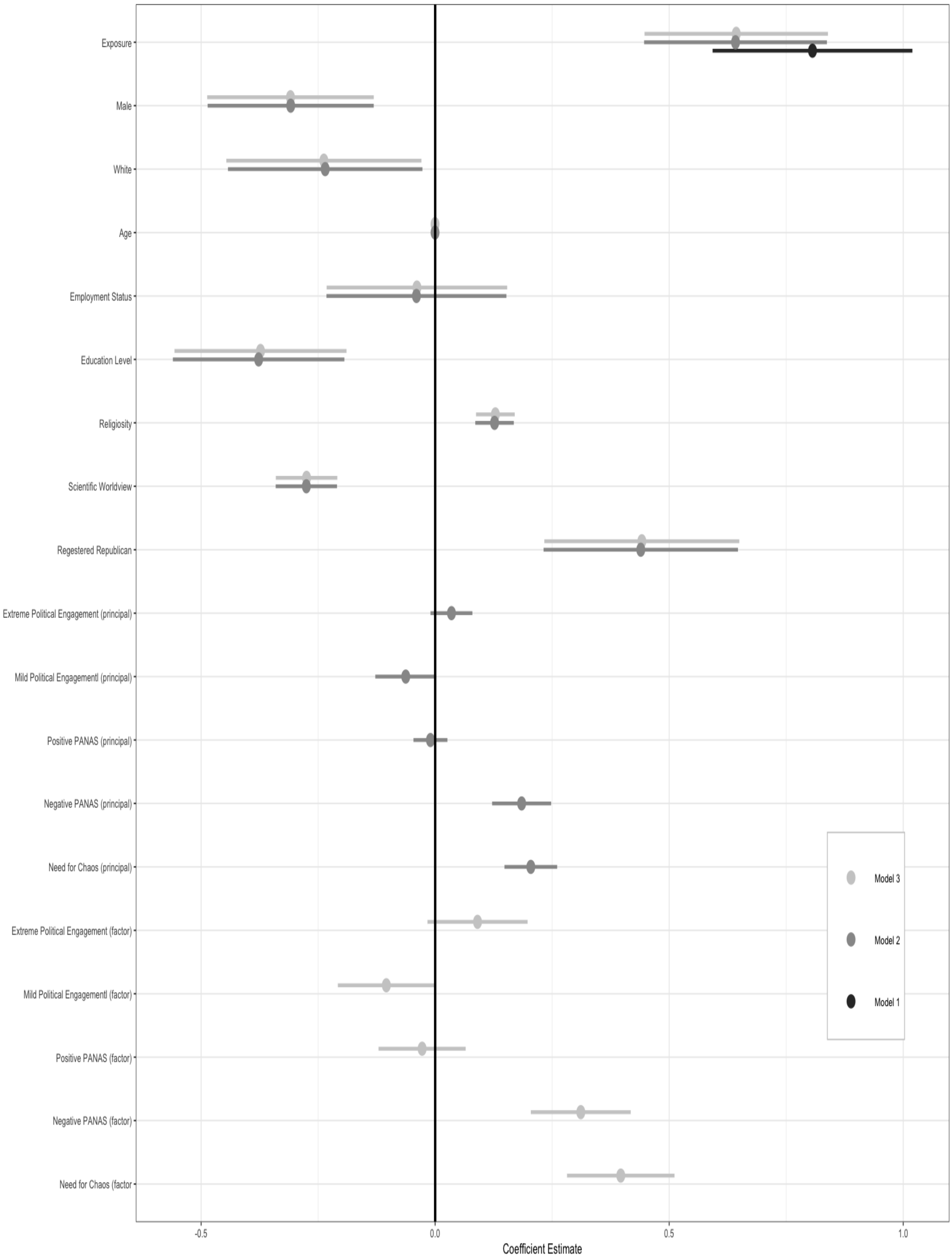
Table 2.2: Hypothesis 1: OLS Regression Results

	Model 1	**Model 2**	**Model 3**
Exposure	0.806	0.642	0.643
	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

While the results are unsurprising their power is interesting. As Figure 2.3 shows, exposure to the conspiracy theory is the largest impact on belief in the deep state of any covariate. The next largest covariate is registered Republican (0.430 in Model 2 and 4.32 in Model 3). This also concurs with the expectations of the literature. The deep state conspiracy theory has traditionally been bipartisan. However, this experiment was fielded in October 2020, just weeks before the 2020 US Presidential Election. In the build-up to the election Republican incumbent, Donald Trump had made numerous claims that the election and more specifically the large volume of expected mail-in-voting would be characterised by widespread voter fraud. While not directly a deep state conspiracy the link is rather obvious. Some form of deep state would be required to undertake widespread fraud. Further, Trump has spent his Presidency criticising the deep state. This would also motivate Republicans to believe in its existence. In the abstract the conspiracy theory is held equally across the left and right, however, this result is unsurprising given the leader of the Republican Party's signalling of its existence.

Figure 2.3: Hypothesis 1: Coefficient Plots



Interestingly, men were less likely to believe the theory than women. There is no identified reason for this in previous research. Different groups respond differently to different conspiracy theories but it is not a clear reason why women would be more receptive to this conspiracy theory. Whites were also less likely to believe the theory. This holds to reason as this is the race that holds the most power in the US. Those with power are less likely to believe in conspiracy theories. Those with at least some college and those who 'identify with the scientific worldview' were also less likely to believe the conspiracy theory. The more educated one is the less likely they are to believe in a conspiracy theory. Similarly, those who profess to believe in the scientific method are less likely to believe an unsubstantiated conspiracy theory. Conversely, more religious people are more likely to believe the theory. This likely follows the inverse logic to those who hold a scientific worldview, especially as religiosity and the scientific worldview are negatively correlated (-.26). Moreover, the politicization of religious liberties especially in the context of Covid-19 and government-mandated restrictions of religious worship may be responsible for some of this relationship. The need for chaos was positively associated with belief in the deep state. This is unsurprising as this battery of questions were largely indicative of anti-establishment tendencies. Finally, those with a negative PANAS in the month leading up to the experiment were more likely to believe the theory. While it would be expected for these individuals to have a more visceral reaction to the emotive frames, the three treatment articles were inherently negative.

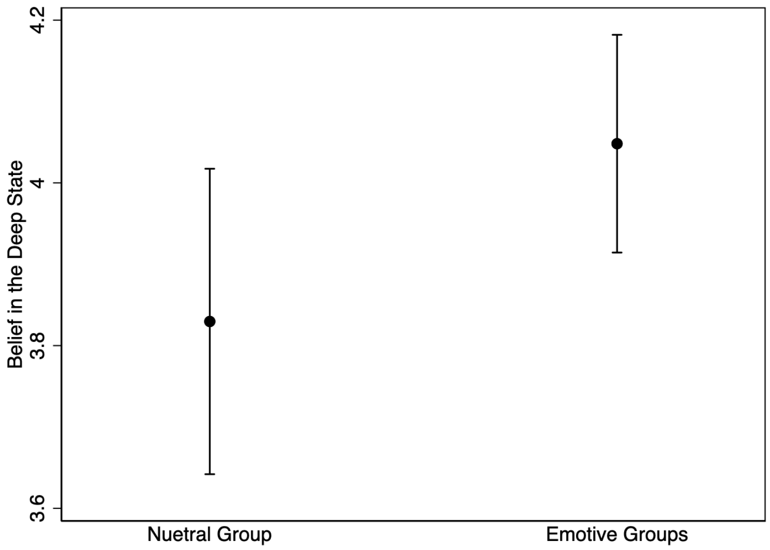
2.4.2 Hypothesis 2

Figure 2.4 shows that the participants who were exposed to the conspiracy theory through a negative emotive frame (M = 4.05, SD = 1.89) compared to the those exposed to the conspiracy theory in a neutral frame (M = 3.83, SD = 1.94) demonstrated a higher belief in the deep state conspiracy, $t(1177) = -1.8762$, $p = .0609$. However, this was not significant at a p-value equal to or less than 0.05.

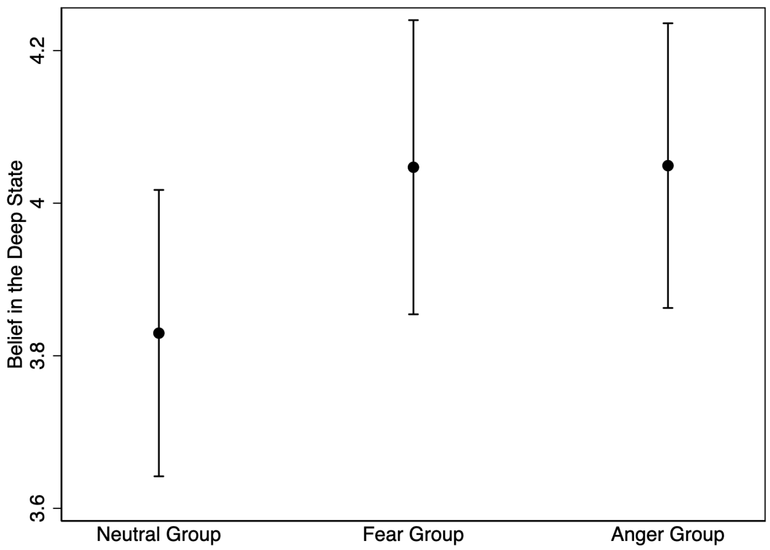
The OLS analysis presented in Table 2.3 is more conclusive than the difference-in-means analysis. All three coefficients are positive The coefficient for Model 4 (no confounding variables) is not significant at the 95 per cent level. The coefficients are statistically significant at the 95 per cent level for both Model 5 and Model 6.

Respondents who were exposed to an emotive frame were either exposed to a fear frame or an anger frame, the literature contends that these emotions will not necessarily have the same impact. Figure 2.4 demonstrates the mean belief belief in the deep state across the the fear (M = 4.05, SD = 1.92) and anger (M = 4.05, SD = 1.86) treatment groups were higher than that of the neutral group (M = 3.83, SD = 1.94). However, neither of these groups demonstrates a statistically significant higher belief in the deep state than the neutral treatment group with the p-values for both relationships below the 95 per cent level (0.1126 and 0.1037 respectively).

Figure 2.4: Deep State Belief - Mean Response



(a) Neutral and Emotive Groups



(b) All Groups

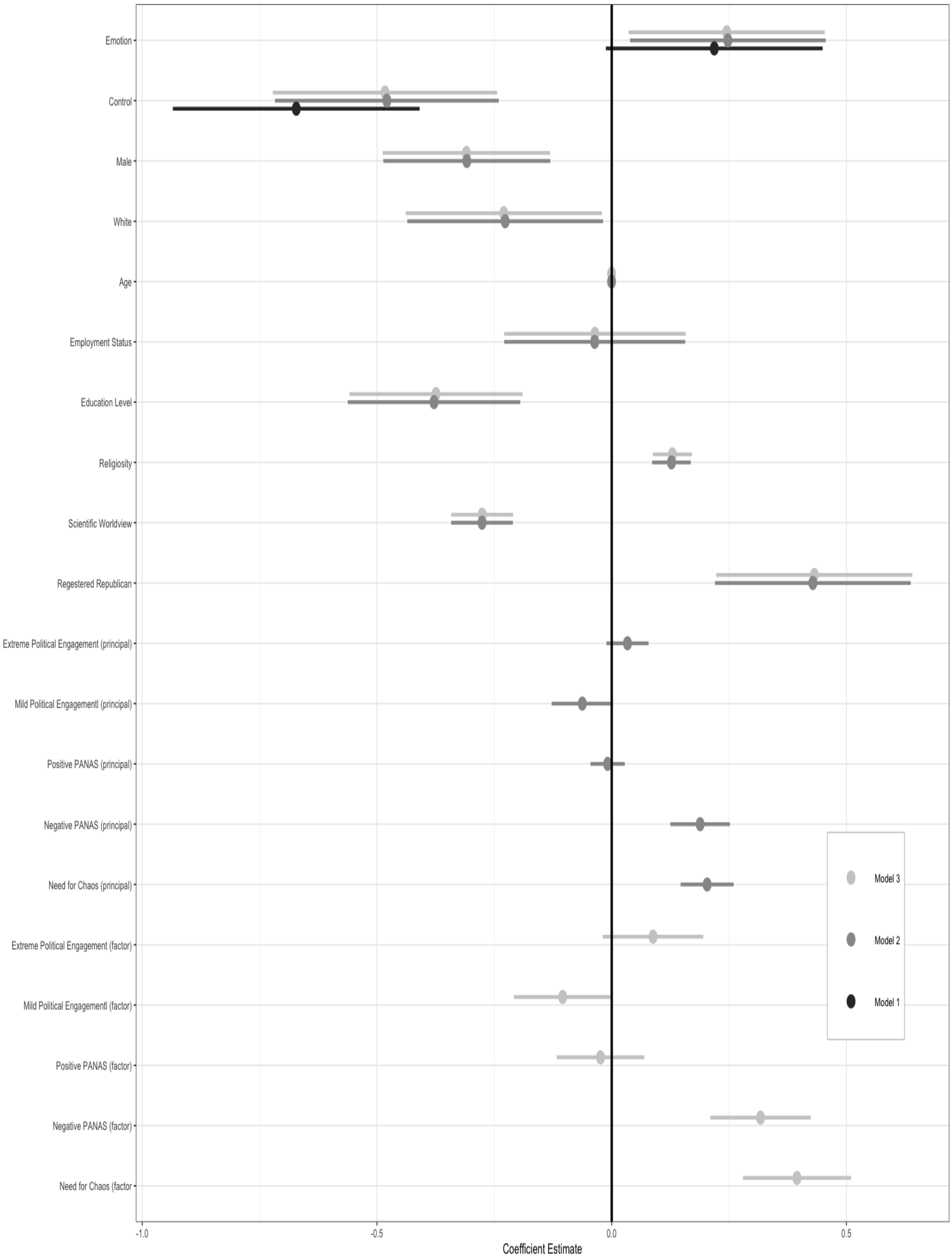
Table 2.3: Hypothesis 2: OLS Regression Results

	(Model 4)	**(Model 5)**	**(Model 6)**	**(Model 7)**	**(Model 8)**	**(Model 9)**
Emotion	0.218	0.247	0.245			
	(0.064)	(0.02)	(0.022)			
Fear				0.217	0.249	0.247
				(0.113)	(0.044)	(0.047)
Anger				0.220	0.245	0.243
				(0.109)	(0.047)	(0.05)

Note: p-values in parentheses

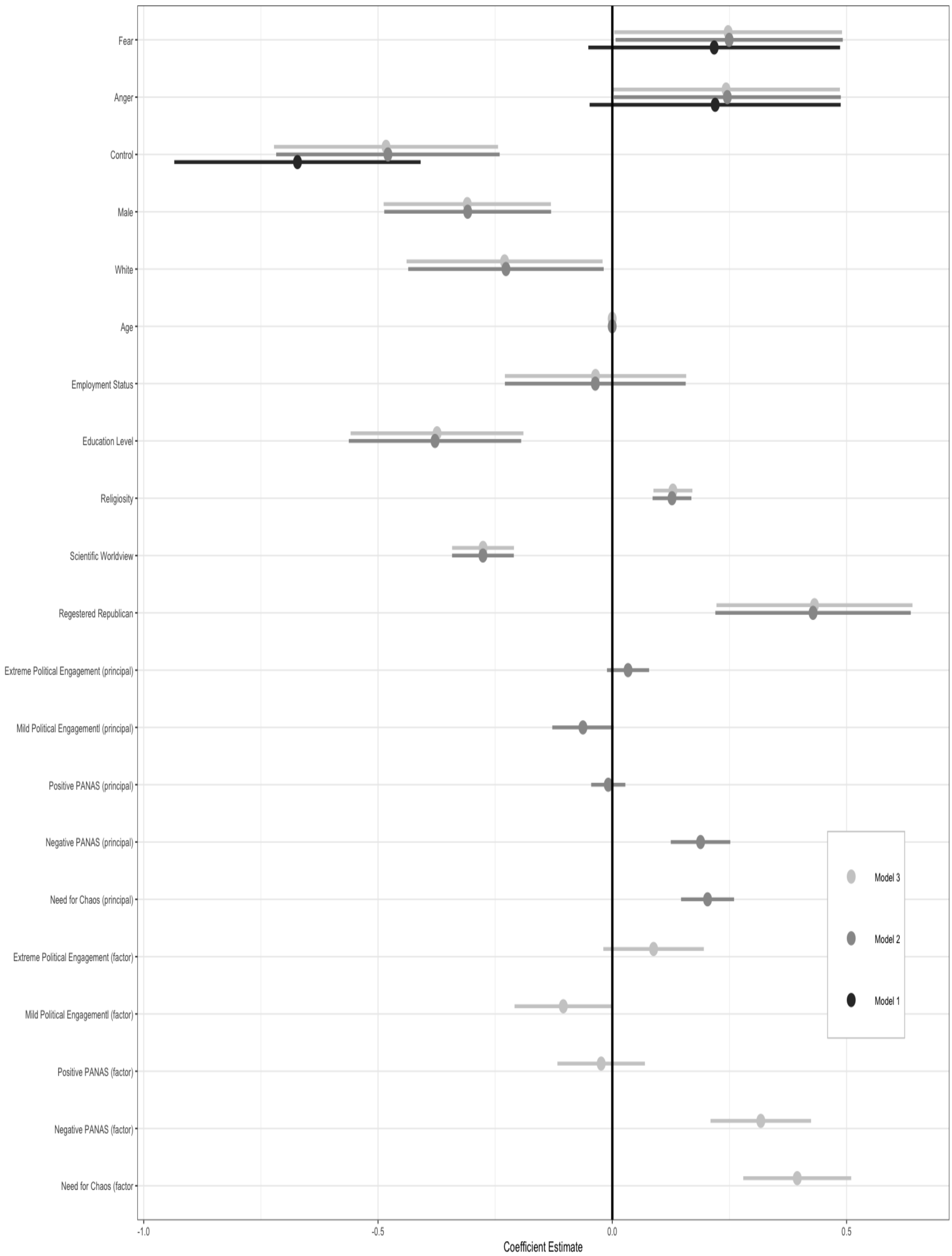
The OLS analysis presented in Table 2.3 is more conclusive than the difference-in-means analysis. The coefficient for the negative emotive frames presented in Model 4 in Table 2.3 shows that when not controlling for confounding variable the effect is not significant at the 95 per cent level. Models 5 and 6 in Table 2.3 demonstrate that when controlling for confounding variables these effect of the negative emotive frames is positive and statistically significant. When examining the effect of individual negative emotions the results follow a similar pattern. Model 7 in Table 2.7 demonstrates that when not controlling for confounding variables, neither fear nor anger have a statistically significant effect at the 95 per cent level. However, as Models 8 and 9 in Table 2.7 outline, both have a positive and statistically significant effect when controlling for confounding variables. Fear has a slightly stronger effect than anger. The full OLS results are in Appendix A.5.

Figure 2.5: Hypothesis 2: Coefficient Plots



(a) Emotion

Figure 2.5: Hypothesis 2: Coefficient Plots (continued)



(b) Fear & Anger

Figure 2.5 shows the coefficient plots for the models presented in Table 2.3. These follow the same pattern as those presented in Hypothesis 1 with Whites, men, those with some college, and those who subscribe to the scientific worldview less likely to subscribe to the deep state conspiracy theory. Conversely, Republicans, the religious, those with a negative PANAS over the past month, and those with a need for chaos are more likely to believe in the conspiracy theory.

In their totality, these results indicate that being exposed to the conspiracy theory through a frame of either fear or anger increases the probability of an individual believing in the theory. Overall, his relationship is slightly stronger for the fear treatment. This would be anticipated by the literature. Fear is a product of the surveillance behavioural system. That is, the fear system monitors the environment for potential threats and motivates individuals to adapt behaviour accordingly. Thus, fear interrupts ongoing behaviour and redirects attention and other cognitive activity towards dealing with the perceived threat that has heightened one's fear. Specifically, it causes people to seek out new information and reconsider courses of action. Anger is seen as a being similar yet distinct of fear. In contrast to fear, anger is more likely to motivate one to cling to prior beliefs and become less receptive to new information (Brader & Marcus 2013). Therefore, the fact that both emotions have an impact but anger's is slightly more muted is not surprising.

2.5 Assessing the robustness of the findings

2.5.1 Manipulation Check

This study aimed to draw a link between exposure to a conspiracy theory through a frame of either fear or anger and belief in that conspiracy theory. An important intermediate step is that the exposure elicits that emotion. That is, those exposed to fear felt fear and those exposed to anger felt anger. This study included a manipulation check. Through a seven-point Likert scale, respondents declared how the article they read made them feel. This manipulation check did not demonstrate any emotional connection between how individuals self declared their emotional state and the article they were exposed to (including the control article). The literature has sited some difficulties in self reporting and how this varies across individuals. However, self reporting has not been identified as being unreliable. Therefore, a major robustness issue for the data presented in this Chapter is an inability to confirm that the manipulation has the desired effect.

2.5.2 Response Validity Indicators

The data for this framing experiment was collected unsupervised through Amazon's Mechanical Turk Crowdsourcing platform. While there is ample literature to suggest that results are perfectly valid using such a method there are also worries that the unsupervised nature of these workers can lead to data validity issues. Therefore, this section addresses these concerns and demonstrates that the quality and validity of the data has not been negatively affected.

While the literature overwhelmingly points to Amazon Mechanical Turk as a source of high-quality data vis-a-vis traditional methods that does not mean it is without fault. Since 2018 there has emerged concerns about 'bots' (algorithms automatically completing tasks) and 'farmers' (individuals using server farms to bypass MTurk location restrictions) (Dreyfuss, Barrett & Newman 2018, Stokel-Walker 2018). Further, inattentive respondents and 'speeders' (respondents seeking to complete the survey as quickly as possible) have always represented an issue for researchers conducting survey-based research with MTurk being no different in this regard (Greszki, Meyer & Schoen 2014, Zhang & Conrad 2014). Thus, before analysing any sample sourced from MTurk, (or any other source for that matter) checks must be undertaken to ensure that the quality of the data being analysed has not been affected by respondents (whether bots or humans) not taking adequate care in their responses (Greszki, Meyer & Schoen 2014, Chmielewski & Kucker 2020).

The literature identifies several '*response validity indicators*'. Namely: (1) lack of comprehension responses; (2) too quick response; (3) response inconsistency; (4) straightlining, statistically improbable responses; (5) disqualified responses; and (6) unusual comments (Greszki, Meyer & Schoen 2014, Chmielewski & Kucker 2020). When there are high levels of these indicators the quality and validity of data can be affected. This would undermine any results returned. Therefore, to evaluate the data quality, all of these validity indicators were thoroughly investigated.

Lack of Comprehension Responses

The literature suggests that framing experiments should include comprehension questions/tests of attentiveness to ensure respondents paid attention to the frame (Berinsky, Margolis & Sances 2014). Indeed, it is of the utmost importance that respondents pay attention to the frame as the entire experiment is based on how respondents interact with the frame. Thus, respondents were asked to answer four comprehension questions about the frame they had been exposed to. To ensure the data collected is of high quality, it is important to analyse the extent to which comprehension questions were answered correctly.

Table 2.4: Treatment Groups Correct/Incorrect Answers by Question

	Correct		**Incorrect**	
Question	**Observations**	**Percent**	**Observations**	**Percent**
Question 1	790	67	389	33
Question 2	830	70	349	30
Question 3	726	62	452	38
Question 4	964	82	215	18

Table 2.5: Control Group Correct/Incorrect Answers by Question

	Correct		**Incorrect**	
Question	**Observations**	**Percent**	**Observations**	**Percent**
Question 1	403	97	13	3
Question 2	381	92	35	8
Question 3	269	65	147	35
Question 4	311	75	105	25

As Tables 2.4 and 2.5 and Figure 2.6 demonstrates that on average the four questions were answered correctly. Question 3 on the treatment articles had the lowest number of correct answers with 62 per cent of respondents answering it correctly, while 97 per cent of respondents answered Question 1 on the control article correctly. While the overall correct answer rate may not be worrying, the level to which the same respondents are answering multiple questions incorrectly must be analysed. It is not unreasonable for a respondent to answer a question incorrectly. However, multiple incorrect answers from the same respondent would imply a lack of attention paid to the frame, the questions, or both. Thus, respondents answering multiple questions incorrectly should be identified and considered for exclusion from the analysis.

Figure 2.6: Correct/Incorrect Answers by Question

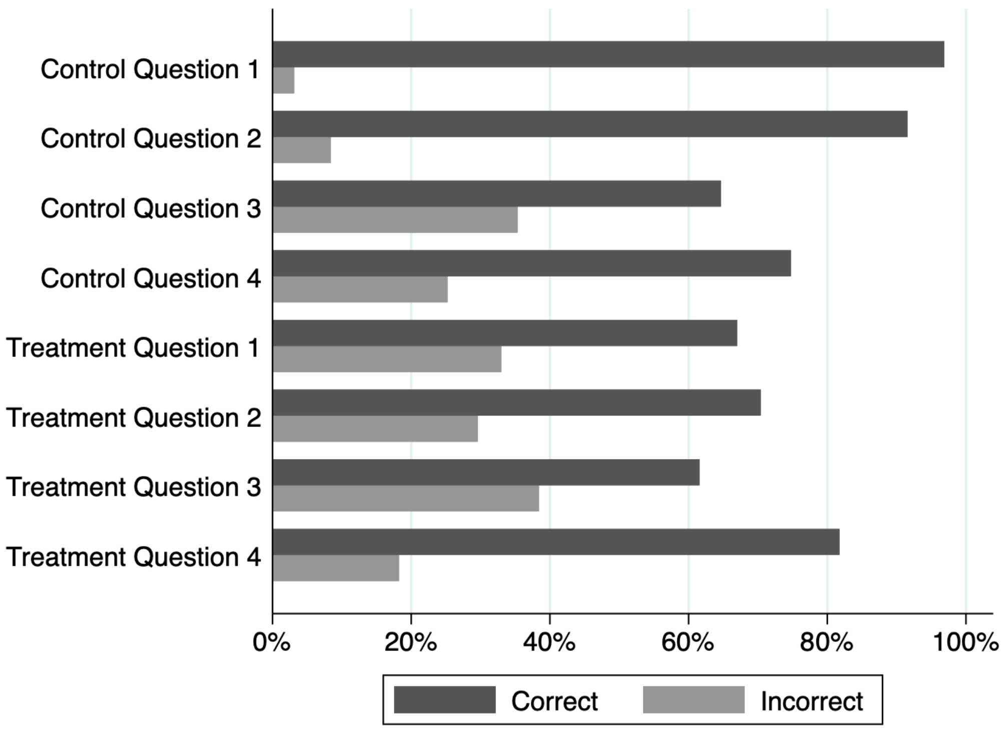


Table 2.6 and Figure 2.7 demonstrate the distribution of cumulative correct answers. Overall, 39 per cent of respondents answered all four questions correctly, with 68 per cent of the sample answering three or more questions correctly and 88 per cent answering at least two questions correctly.

Table 2.6: Cumulative Correct Answers

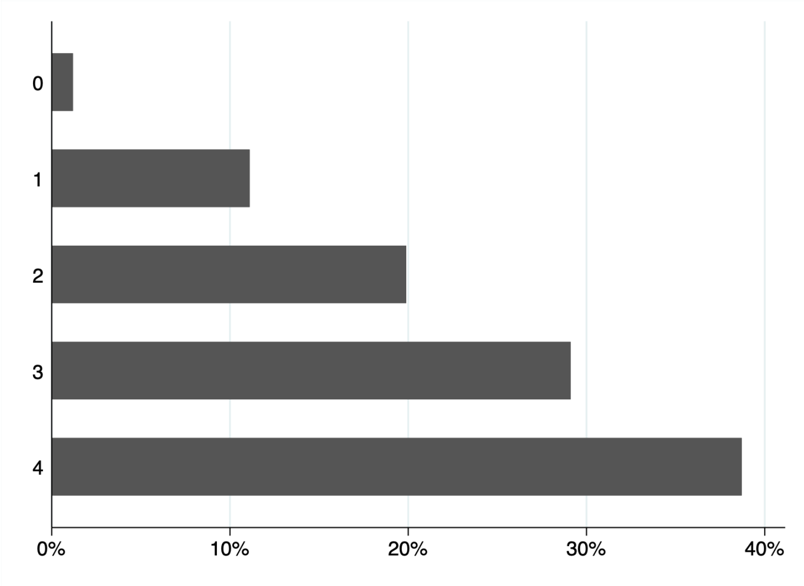
Number of Questions Answered Correctly	**Observations**	**Percent**
Zero	19	1
One	177	11
Two	317	20
Three	464	29
Four	617	39

As previously stated, it is not unreasonable for respondents to have answered one question incorrectly. While there is no ‘rule’ for excluding participants based on the number of comprehension questions answered correctly, respondents who answered less than two questions correctly should be eliminated (Berinsky, Margolis & Sances 2014). Indeed, if a respondent were to guess or randomly answer for all four questions probability would suggest they ought to get at least one question correct.[7] Of course, drawing the line at one incorrect question may lead to the inclusion of respondents who were not paying adequate attention to the frame. However, any other cut-off point would be far more arbitrary than the one selected.

The OLS results based on this exclusion criteria can be seen Appendix A.5. Overall, There is no significant change in the results returned therefore, in the analysis presented in this Chapter no respondents were excluded for a lack of comprehension.

[7]There are four questions with four options each. Thus, the probability of randomly getting any question correct is 0.25. 4 x 0.25 = 1. Thus, a respondent who guesses or randomly answers each question will likely get a single question correct.

Figure 2.7: Correct/Incorrect Answers by Question



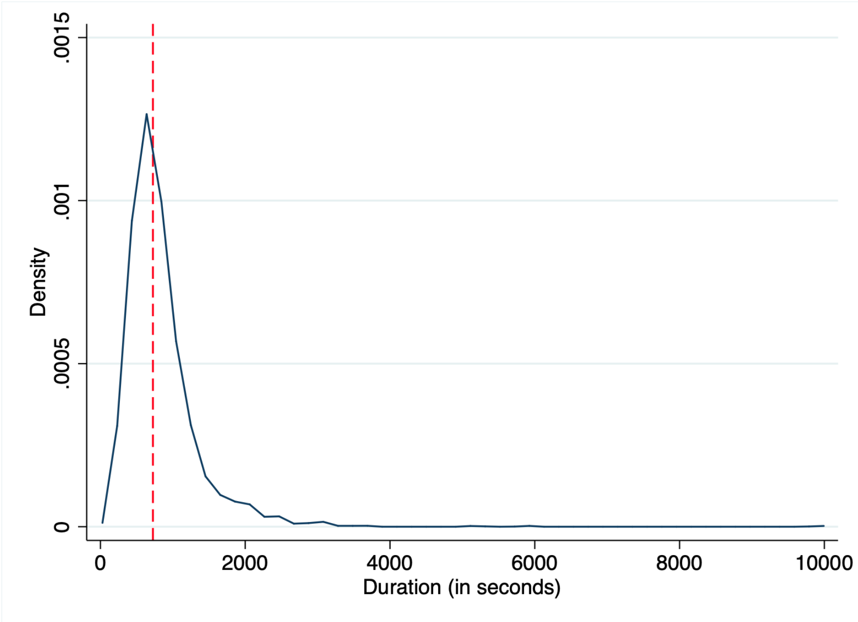
Too Quick Responses

One of the benefits of delivering online surveys and experiments is that the lack of an interviewer reduces the incidence of 'social desirability bias' answers (Greszki, Meyer & Schoen 2014). That is, respondents answering in a manner that they think will be viewed favourably by others (Nederhof 1985). However, the absence of the interviewer leaves the process uncontrolled and data quality may suffer as a result (Groves, Fowler Jr, Couper, Lepkowski, Singer & Tourangeau 2011). In particular, measurement errors resulting from inattentive respondents may be of particular concern to researchers. One method the literature has used as an indicator of data quality is response time as particularly quick response times might indicate low data quality (Greszki, Meyer & Schoen 2014).

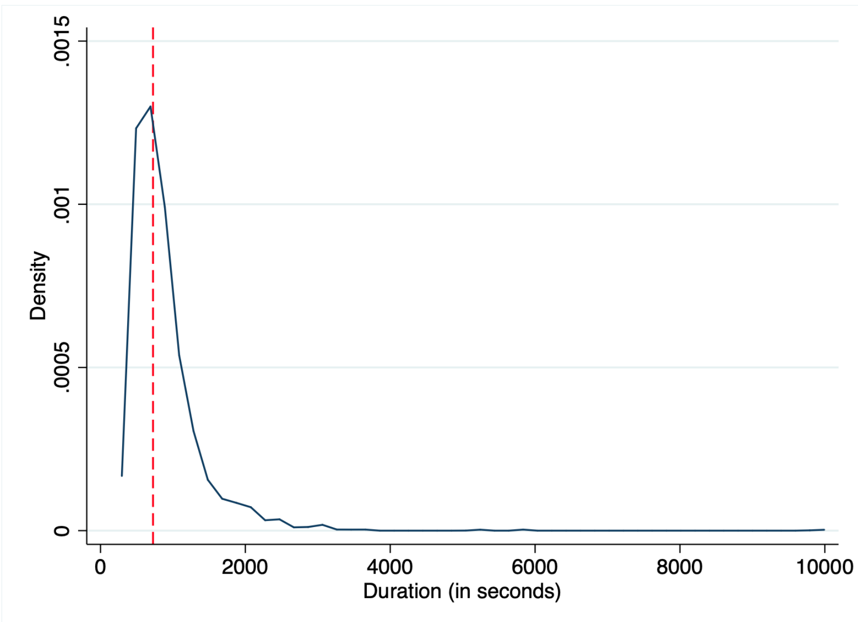
The process of answering a survey question comprises of four steps. A respondent must first read the text of the question to comprehend the question being asked. Therefore, reading only responses (a common occurrence for speeders) leads to invalid answers. Once the question has been read the respondent has to access the relevant information in their memory before forming a judgement. Finally, the respondent formulates a response, either through selecting an option or filling out a text box. While all steps may not always be necessary, step one and step four are required to formulate an accurate answer. Thus, it does take some time to answer each question accurately (Greszki, Meyer & Schoen 2014).

To date, the literature has no set rule on how to deal with respondents who fill out surveys too fast. However, evidence suggests that identifying respondents who have answered the survey significantly faster than the median is the best way to approach this issue. As Figure 2.8 demonstrates, response time is skewed to the right with some extreme outliers. These outliers do not represent a problem as these respondents took a long time to answer the survey and therefore the quality of these responses should not be in question. However, these outliers cause the mean to become relatively high. Thus, the median is used as the benchmark, rather than the mean.

Figure 2.8: Response Time Density Plots (with median)

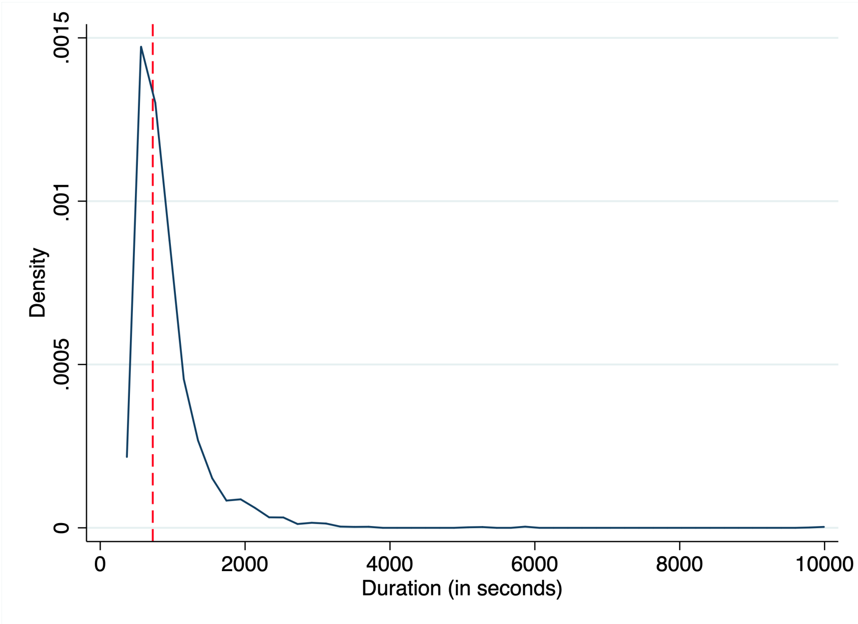


(a) Response time density plot

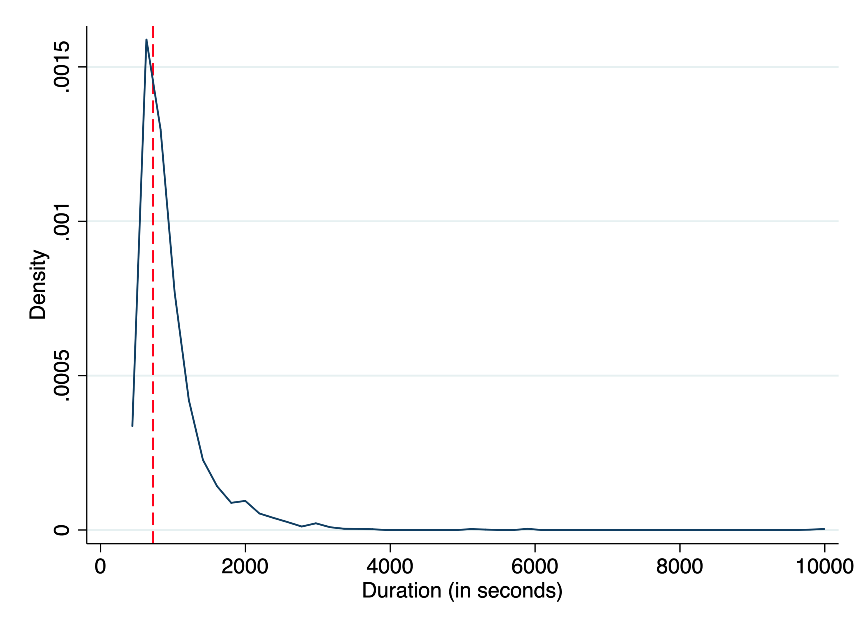


(b) Response time density plot (excluding those 50% faster than the median)

Figure 2.9: Response Time Density Plots (with median) (continued)



(a) Response time density plot (excluding those 40% faster than the median)



(b) Response time density plot (excluding those 30% faster than the median)

As the literature suggests response time may influence data quality it is prudent to examine respondents whose answers were particularly fast. However, selecting which respondents are classified as having completed the survey too fast is not straightforward and any choices made here is somewhat arbitrary. If a researcher eliminates too many respondents the power of the survey is reduced and high-quality data is excluded. If too few respondents are excluded then the validity of results is reduced as low-quality data remains in the dataset. Further, researchers need to ensure that any decision made when excluding respondents is fully justified to avoid accusations that thresholds were selected as they returned the most favourable results (Greszki, Meyer & Schoen 2014). Thus, selecting and exploring multiple thresholds is recommended. This chapter selected three categories. Namely, excluding those who responded 30, 40, and 50 per cent faster than the median. Table 2.7 and Figure 2.3 demonstrate the impact that these exclusion criteria have on the sample.

Table 2.7: Response Time Categories

Exclusion Criteria	**Observations**	**Percent**
30% faster than the median	343	20
40% faster than the median	223	14
50% faster than the median	126	8

The OLS results based on this exclusion of those 50 per cent faster than the media (i.e., the most egregious ‘speeders’)can be seen Appendix A.5. Overall, there is no significant change in the results returned therefore, in the analysis presented in this Chapter no respondents were excluded for too quick responses.

Response Inconsistency

One common method used to identify inattentive respondents is if they demonstrate inconsistency in their answers. For instance, a survey may ask a respondent their age range, and at a later point ask the respondent to type their age into a text box. If these two answers do not match it can be assumed that the respondent is not paying adequate attention to the survey questions (Chmielewski & Kucker 2020). Thus, respondents were twice asked about voting preference in the US Presidential election. These questions were as follows:

1. If there was a Presidential election today, which candidate would you vote for?

    (a) Donald Trump (**R**)

    (b) Joe Biden (**D**)

    (c) Third Party

    (d) Don't know/no preference

    (e) Would not vote

2. If there was a Presidential election today, which party would you vote for?

    (a) Republican Party

    (b) Democratic Party

    (c) Third Party

    (d) Don't know/no preference

    (e) Would not vote

Given that this framing experiment was put into the field on 02 October 2020 and there was a Presidential Election on 03 November 2020 it is safe to assume that respondents who say they will vote for Biden or Trump should state that they will vote Democrat and Republican respectively. Sometimes the 'generic' ballot (where voters are asked based on party rather than candidate) can differ. However, given the proximity of the election, the candidates and the parties can be considered one and the same. 9 respondents answered these questions inconsistently.

The OLS results based on excluding those who answered in an inconsistent manner can be seen Appendix A.5. Overall, there is no significant change in the results returned therefore, in the analysis presented in this Chapter no respondents were excluded for a lack of consistency.

Straightlining

Straightlining occurs when survey respondents give identical, or close to identical, responses to questions using the same response scale (such as a 7 point Likert scale) and this may reduce data quality (Herzog & Bachman 1981). Instead of expending cognitive effort to carefully think about each question, straightliners might give the same, or almost the same answer to all items within a battery of questions. Investigating the prevalence of this behaviour is important as it may undermine the reliability and validity of survey responses. Further, it can also inflate the correlations between items in the battery of questions, which suppresses the researcher's ability to investigate the real differences between the responses (Kim, Dykema, Stevenson, Black & Moberg 2019). This survey contains three battery of questions, which would be susceptible to straightlining. These batteries are shown in Tables A.2, A.3, and A.4 in Appendix A.4.

Despite its potential importance to the quality of any survey or experiment in both social science and the natural sciences, straightlining has been understudied and the literature does not provide a single standard technique to measure straightlining (Kim et al. 2019). There are five distinct indices researchers have used to measure straightlining. An overview of these is provided in Table 2.8.

Simple nondifferential method. This method calculates the percentage who use only a single response category within a battery of questions. The larger the proportion the more straightliners there are.

Mean root of pairs method. This computation requires three steps. First, produce a temporary index by computing the mean of the root of the absolute differences between all pairs of items in a battery for all respondents. The formula is as follows:

$$(1)\ X_{temp} = \frac{\sqrt{|q_1-q_2|}+\sqrt{|q_1-q_3|}+\sqrt{|q_1-q_4|}+...+\sqrt{|q_1-q_n|}+...+\sqrt{|q_{n-1}-q_n|}}{n}$$

Table 2.8: Overview of Straightlining Measures

	Measures of Nondifferentiation			Measures of Variation	
Dimension	Simple Nondifferentiation Method	Mean Root of Pairs Method	Maximum Identical Rating Method	Standard Deviation of Battery Method	Scale Point Variation Method
Computation	Proportion of respondents using a single response category	Mean of the root of the absolute differences between all pairs of items in a battery	Proportion of the maximum number of identical ratings in a battery	Standard deviation (or variance) of ratings for each respondent	Probability of differentiation: $P_d = 1 - \sum P_i^2$
Range	0.00 – 1.00	0.00 – 1.00	0.00 – 1.00	0.00– greater than 0.00	0.00 – 1.00
Relevant studies	Herzog and Bachman (1981) and Krosnick and Alwin (1988)	Chang and Krosnick (2009), Fricker et al. (2005), and Couper et al. (2013)	Holbrook et al. (2003) and Tourangeau et al. (2004) and Shrum	Krosnick and Alwin (1988) and McCarty and Shrum (2000)	Krosnick and Alwin (1988), McCarty and Shrum (2000), and Heerwegh and Loosveldt (2008)

Source: *Kim et. al 2019*

Next, rescale the temporary index to range from 0 (least straightlining) to 1(most straightlining). This gives a measurement for the extent to which each respondent straightlined. The formula is as follows:

$$(2)\ X_{index} = \frac{Respondent\, X_{temp} - max(Respondent\, S_{temp})}{min(Respondent\, S_{temp}) - max(Respondent\, S_{temp})}$$

The final step is to simply retrieve the mean of all the indexes in the sample. This gives a measurement for the incidence of straightlining in the sample as a whole. The formula is as follows:

$$(3)\ \text{Mean root of pairs index} = \frac{X_{index} + Y_{index} + ... + n_{index}}{n}$$

Maximum identical rating method. The maximum identical rating method identifies which value is most commonly used by the respondent and then determines for what proportion of items that value was selected by the respondent. Because it is a proportion its value ranges from 0 (least straightlining) to 1 (most straightlining) for a given respondent. The value for the sample as a whole is the mean of maximum identical rating for all respondents.

Standard deviation of battery method. The standard deviation of battery method measures the standard deviation (or variance) of the battery of questions for each respondent. The higher the score the less straightlining.

Scale point variation method. Sometimes called *rho*, the scale point variation method is defined as $1 - \sum P_i^2$ where p_i is the proportion of values rated at each scale on a rating scale and i indicates the number of scale points. If respondents use more scale points within a battery, the measure becomes larger, so that higher scores indicate less straightening.

Table 2.9: Overview of Straightlining Measures for PANAS

Straightline Measurement	Mean	Median	Standard Deviation	Minimum	Maximum
PANAS					
Mean root of pair method	.28	.25	.16	.01	1
Maximum identical rating method	.47	.42	.12	.25	1
Standard deviation of battery method	1.11	1.08	.39	0	2.09
Scale point variation method	.63	.65	.11	0	.79
ARIS					
Mean root of pair method	.29	.27	.17	0	1
Maximum identical rating method	.45	.42	.16	.17	.83
Standard deviation of battery method	1.33	1.32	.71	0	3.16
Scale point variation method	.56	.62	.2	0	.84
Emotional response to frame					
Mean root of pair method	.34	.32	.19	0	1
Maximum identical rating method	.31	.25	.13	0	.58
Standard deviation of battery method	2.03	1.99	1.16	0	4.81
Scale point variation method	.57	.61	.22	0	1

There were six, ten, and 49 respondents who used only a single response category in the Positive and Negative Affect Scale (PANAS), emotional response to frame, and AINS batteries respectively. It would be tempting to simply drop these respondents as the lack of variation in their responses implies there was no attention paid to the answers. However, these figures need to be looked at in greater detail. Seven respondents straightlined in the emotional response to the frame battery of questions. For the PANAS battery, one respondent marked ‘all of the time‘ for the twelve questions in the battery, one marked ‘most of the time‘, and the remaining four all marked ‘none of the time‘. These responses demonstrate a lack of attention to the questions as the responses contradict themselves.

Four respondents, four respondents, and one respondent said that the article elicited a 2, a 4, and a 10 for all emotions. Given the varied emotions in this battery, only respondents who felt no emotion should be straightlining.

The Activism and Radical Intention Scale (ARIS) battery of questions cover mild (joining a political cause or donating money to that cause) to radical political activism (engaging in political violence). Straightlining can reasonably occur when a respondent neither agrees nor disagrees, strongly agrees, or strongly disagrees with the statements. It is reasonable for someone who would go to war for a cause, to also join an organisation that fights for that cause. Similarly, someone who would not join an organisation that fights for a cause is also highly unlikely to be willing to go to war to fight for that cause. Similarly, holding no opinion (in the form of a neither agree nor disagree response) is also acceptable. Therefore, straightlining for extreme responses can be viewed as acceptable. Thus, upon further investigation, 43 respondents straightlined in what can be considered an implausible manner.

As outlined in Table 2.9, the results across the three batteries of questions for the mean root of pair method, maximum identical rating method, the standard deviation of battery method, and scale point variation method indicate that, while not perfect, the variation in responses was not particularly low. Of course, within the responses, there will be respondents who demonstrate little variation in their responses. However, as discussed, the data contains cases where straightlining is plausible. Differentiating between respondents whose low-variation responses were beyond an arbitrary cut-off point, but were plausible and those whose responses were implausible would be a difficult if not impossible task. Given the moderate scores returned for the four methods across the three batteries, as well as only nine respondents implausibly straightlining, straightlining was not deemed to have had a major impact on data quality (Schonlau & Toepoel 2015).

Therefore, only the 58 implausible straightliners were identified and investigated. The OLS results based on excluding 58 implausible straightliners can be seen Appendix A.5. Overall, there is no significant change in the results returned therefore, in the analysis presented in this Chapter no respondents were excluded for a lack of consistency.

Statistically Improbable Responses

Statistically improbable results are those that simply do not make sense. For instance, if a respondent was reported to have more than ten children or more than four children of a similar age. These responses are not impossible, but they are improbable (Chmielewski & Kucker 2020). This framing experiment contained one question where statistically improbable responses could have been returned. This was an open-ended question asking respondents their age. There were several respondents in their seventies and one whose stated age was 88. While these ages seem unlikely given the platform used for data collection they are by no means impossible. Therefore, there were no statistically improbable responses.

2.5.3 Disqualified Response and Unusual Comments

There were no disqualified responses in this chapter. This survey contained two open-ended questions. These simply asked what the respondent's male and female guardian's profession is/was. There were no unusual comments returned.

Overall, there did not appear to be any material impacts of data quality and validity on the results presented in this Chapter.

2.5.4 Ordinal Logistic Regression

The dependent variable of this chapter is a seven-point Likert scale ranging from strongly disagree to strongly agree. One approach to such an analysis is to use an Ordinal Logistic Regression (OLR). Given there are seven points on this scale there is sufficient variation to proceed with OLS rather than OLR. However, for transparency the OLR results are provided in Appendix A.6. There is no substantive impact on the results between the two statistical models.

2.6 Conclusion

This chapter examines how individuals respond to a conspiracy theory presented to the through varying negative emotive frames (fear, anger, and neutral). The aim was to identify if exposure to conspiracy theories through fear and anger made individuals more likely to believe a conspiracy theory.

The results presented in this chapter are unclear. Results are not statistically significant for either fear or anger across all models presented. Further, there is serious doubt over the effect that the manipulation had on the subjects. This is a significant limitation to the findings presented here.

The effect does exist for both fear and anger in the models which include confounding variables. The presence of this effect in a large and diverse sample such as this would have important implications for several reasons. First, there is a suggestion that society is becoming less accepting of elite narratives and more inclined towards conspiratorial thinking. The literature on this is by no means settled. However, we do observe trends such as the rise of right-wing populist parties, a decline in the uptake of vaccine programs, and the rejection of public health advice during the Covid-19 pandemic (Uscinski & Parent 2014, Uscinski et al. 2020). Therefore, understanding how people come to form conspiratorial opinions is important for two reasons. First, knowing how these opinions can assist authorities in stopping the spread of these theories. Secondly, in the absence of this, knowing how opinions were formed can assist in reversing them. Reversing conspiratorial beliefs is notoriously difficult. However, part of the puzzle is understanding how the opinion was developed in the first place. This chapter makes an important contribution to the overarching goal of reversing citizens' conspiratorial opinions.

Further while the presence of an effect would have important implications for the study of conspiracy theories as well as misinformation and disinformation more generally it must be noted that these results were generated by abstract research design. Respondents were randomly exposed to a once-off article while working as a Mechanical Turker. The real-world information environment is much more complex than this and involves many iterations of informational exposure across multiple sources and multiple time periods. These results offer a valuable insight into the powerful role that negative emotive frames play in the development of conspiratorial opinions. Indeed, if this process was repeated over time the effect might be even stronger. Similarly, the effects presented may quickly disappear.

The findings presented here raise the need for further research into the link between negative emotive frames and conspiratorial through a more comprehensive experimental approach.

There is little doubt that fringe conspiracy theorists in the United States are highly associated with the "shock jock" and outrage media culture. Thus, it would not be surprising if they do indeed use negative emotions to convince their audiences of their point of view. This chapter tried and came up short in answering the first part of the puzzle, that fear and anger do influence individuals' perceptions of conspiracy theories. The next step is to evaluate whether in the "real world" conspiracy theorists utilise heightened levels of fear and anger and whether this has any impact.

Chapter 3

The Presence of Negative Fear and Anger in Conspiratorial Messaging

Abstract

An important factor influencing individuals' perception of conspiracy theories is their exposure to these theories. This is both intuitive and widely noted in both the conspiracy theory and political communication literature. Further, there is ample evidence to suggest that when individuals are exposed to new information through a negative emotive frame (e.g., fear and anger), they are more likely to believe this information and to develop stronger feelings on the subject. This chapter posits that conspiracy theorists take advantage of this mechanism. That is, those spreading conspiracy theories use fear and anger within their messaging given the profound effect this has on their audience's opinion formation. The presence of fear and anger within conspiracy theories is studied through Facebook data, news articles, and news headlines. Through Facebook's Crowdtangle platform, the Webhose web scraping service, the Media Bias Fact Check dataset, and the and the National Research Council Canada Emotion Lexicon, this chapter demonstrates that conspiracy theorists are more likely to use heightened levels of fear and anger in their social media posts and news headlines, but not their news articles.

3.1 Introduction and Motivation

One of the most useful ways to understand the pervasive nature of conspiracy theories in American society is to understand how people acquire these beliefs in the first place. Most of the knowledge any individual has acquired is not gained through personal or direct information. We rely on others for our information (Gopnik 1993). Traditionally, this came through the news media. However, in recent times this information has been provided through the internet and especially social media networks (Jacobi, Van Atteveldt & Welbers 2016). In certain domains, people suffer from what can be described as a crippled epistemology. That is, they know very few things and what they know is wrong (Paquet 2009). This is observed in the context of extreme beliefs. These beliefs stem not from irrationality but from having the wrong information. Thus, the extreme views are supported based on the wrong information (Hardin 2002). This phenomenon can be observed in the context of conspiracy theories (Sunstein & Vermeule 2009). For example, individuals who believe that Covid-19 vaccines are harmful may be responding rationally to the information signals that they received.

Conspiracy theories originate from many different sources. However, an important factor that helps them become popular is the intentional spread of the theories by conspiracy entrepreneurs (Sunstein & Vermeule 2009). Such entrepreneurs may be sincere in their beliefs or may propagate conspiracy theories for profit. Famous examples of such entrepreneurs are Alex Jones, Tucker Carlson, David Icke, and Thierry Meyssan. If, as the results presented in Chapter 2 suggest, the presence of fear and anger influences individuals' perceptions of conspiracy theories then it is important to investigate whether or not those propagating conspiracy theorists utilise these negative emotions in their messaging. This gives rise to the following research question:

RQ: Do conspiracy theorists use more fear and anger in their messaging than their non-conspiratorial peers?

To investigate this research question this chapter examines the presence of negative emotive language in US-based news outlets' Facebook posts, news articles, and news headlines. In doing so, this chapter demonstrates that conspiracy theorists use significantly more negative emotive language in their Facebook posts and news headlines, but interestingly, not in their news articles. Importantly, this Chapter only looks at conspiracy theorists as a whole and does not isolate conspiratorial messaging. Thus, a natural next step in this research is to isolate Facebook posts and news articles that directly deal in conspiracy.

3.1.1 Negativity, Emotionality, and the News Media

The literature is in relative agreement that reporting on negative news stories is far more popular than reporting on good news stories (Graber & Holyk 2011). There is no consensus as to exactly what causes this to happen. Negative news stories catch our attention far more than good news stories (Garz 2014, Soroka, Fournier & Nir 2019). While in the context of the news media, a good news story is often the absence of an event while a bad news story is the occurrence of an event. The news media does not report a list of celebrities who have not died in the past day, they do not report on the countries where war has not broken out, they do not report on cities where a bomb has not gone off, and they do not report on the lack of a political scandal. They do, however, report on the death of a celebrity, the outbreak of war, the bombing of a city, and a scandal engulfing a politician (Arango-Kure, Garz & Rott 2014). Therefore, some argue that there is a natural bias built into the reporting of news (Nelson 2011).

Many academics argue that this does not tell the full story. The news media is overwhelmingly negative and this goes beyond any variation that can be explained by the bias of the occurrence of bad news (Soroka, Fournier & Nir 2019). Indeed, recent research on the coverage of the Covid-19 pandemic found that independent of the situation in the United States, coverage by the news media of the pandemic was almost always negative. It did not matter when objectively good news stories such as advancements in the vaccine programs or reducing case numbers were occurring the news remained negative (Hart, Chinn & Soroka 2020, Sacerdote, Sehgal & Cook 2020).

There is some debate as to what drives this. Is it a supply-side issue? Or, do we as consumers of the news, demand more negative news? That is not to say that we make a conscious effort to choose the negative stories presented to us. But while we generally see ourselves as positive people the bad experiences we have tend to stick in our mind clearer than the positive (Brader & Marcus 2011, Soroka, Fournier & Nir 2019). For example, one study amongst French students found that when asked to recall an emotional moment in their life three-quarters of participants cited a negative experience with only one quarter citing a positive one. A similar result was found amongst Americans. We then engage with the news media more when it comes to negative stories rather than positive stories. This demand-side interaction leads news reporters and their editors to prioritise the negative stories (Gunter 2015, Soroka, Fournier & Nir 2019).

3.1.2 The Communication of Conspiracy Theories

How conspiracy theories are communicated is an understudied aspect of the conspiracy theory literature. Much of the effort has been put into understanding what motivates individuals to believe in conspiracy theories. However, the other side, that of those propagating conspiracies has remained understudied. Even when studying the communication of conspiracy theories much of the literature focuses on the need the conspiracy theory fills. For example, as ways to explain intergroup relations, to challenge power structures and assumptions about power structures, help groups cope with threatening situations, a response to major political events, reinforce ideological biases, help make sense of events that threaten existing worldviews. Further, the political motives of those who spread conspiracy theories have been studied. An example is the British Nationalist Party use of anti-Islamic conspiracy theories to create the conditions for ideological extremism to exist. But of course, the motivations can vary from group to group and from conspiracy to conspiracy (Sunstein & Vermeule 2009, Douglas et al. 2019).

While much of the work on communication of conspiracy theories has focused on the who and where there has been some limited work on the stylistic nature of conspiratorial communication. We know that those advocating conspiracy theories tend to focus more on undermining official narratives rather than advocating for their alternative accounts. Those arguing against ca conspiracy theory do the opposite. They spend more time building up their argument and less time attacking the conspiracy theory (Wood & Douglas 2013). Research also suggests that conspiracy theorists are more likely to demonstrate information from both sides of the argument in an effort to come across as more moderate (Grant, Hausman, Cashion, Lucchesi, Patel & Roberts 2015). There is some evidence that conspiracy theorists try to present themselves as rational and open-minded (Wood & Douglas 2013). However, there is a lack of studies in this area. One study that used content analysis on comments responding to a pro-vaccine post by Mark Zuckerburg found that the language used by anti-vaccination was more analytical, less authentic, less anxious, and the language was less tentative. However, the study comprised of 1,500 comments. A relatively small-N analysis. Thus, despite the origins of the study of conspiracy theories in the United States citing the paranoid style of American politics we still know relatively little about the style of conspiratorial communication (Hoffman, Felter, Chu, Shensa, Hermann, Wolynn, Williams & Primack 2019). In contrast, Klein, Clutton, and Dunn (2019) find that Reddit users who engage in conspirational posting use heightened negative emotive language. This study did not find evidence beyond non-specific negative emotions. Thus, the role of individual emotions is, as of yet, unknown in the literature.

3.1.3 Negative Emotion and Conspiratorial Messaging - A New Large-N Analysis

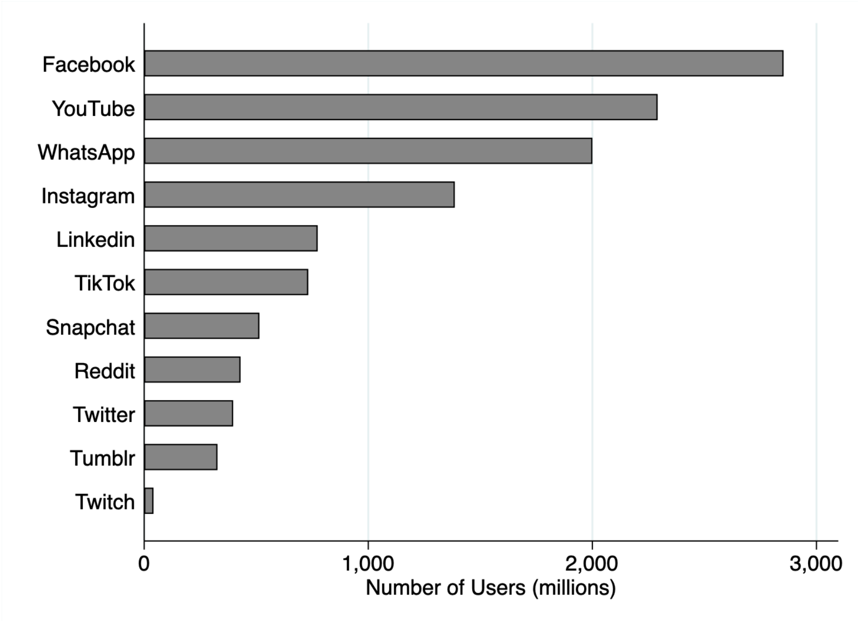
There is some anecdotal evidence that conspiracy theorists often present their theories through a negative emotive frame. The same observation has been made in the context of urban legends with people who read sensational stories designed to 'gross them out' more likely to arouse their emotions. Intuitively this relationship makes sense in the context of conspiracy theories. Whether for monetary benefit or for genuine belief, conspiracy theorists and entrepreneurs aim to undermine a particular group of people, processes, or institutions. At no point are they trying to build something up. The aim is to undermine some group in society that is perceived to be abusing its power. Thus, in this case, the use of negative emotion is an appropriate communication strategy (Sunstein & Vermeule 2009). Indeed, given how overwhelmingly negative the news environment is one would expect those propagating conspiracies to have to go even more negative in order to get their message across. Despite the ample evidence on the role that negative emotion plays in opinion formation, as well as the suggestions that it is present in conspiratorial messaging, the impact of the use of this negative emotion has never been systematically studied at a large scale in the literature.

This chapter creates a new dataset of the publicly available Facebook posts of all US-based news media organisations from 01 January 2020 to 31 January 2021. As Figure 3.1 illustrates, Facebook is the globe's most popular social media site (3.1(a)), has a low partisan difference amongst users (3.1(b)), is the most common social media site through which individuals' receive their news (3.1(c)), with nearly half of Americans getting their news from social media platforms at least some of the time (3.1(d)). Therefore, Facebook is an appropriate information source to study. With a corpus of 7,221,509 Facebook posts, this is the largest analysis of the stylistic elements of conspiracy theorists communication strategies to date.

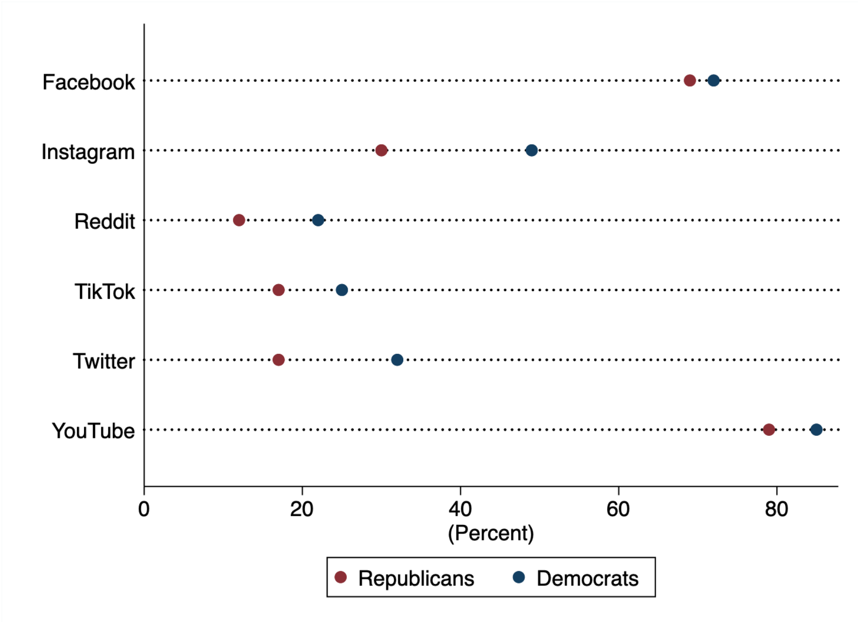
The study of Facebook posts is supplemented by an analysis of news articles from a selection of right-wing news outlets. This is done to give a more granular look at how conspiracy theories are communicated. News articles are naturally longer than Facebook posts. Thus, including articles allows for a more in-depth analysis of the messaging style. The headlines are also analysed as there is evidence to suggest that headlines are often the most important aspect of a news article when triggering individuals (Geer & Kahn 1993, Ecker, Lewandowsky, Chang & Pillai 2014).

This chapter specifically investigates the extent to which conspiracy theorists utilise heightened fear and anger in their messaging. To this end, the following hypothesis is tested:

Figure 3.1: Social Media Usage

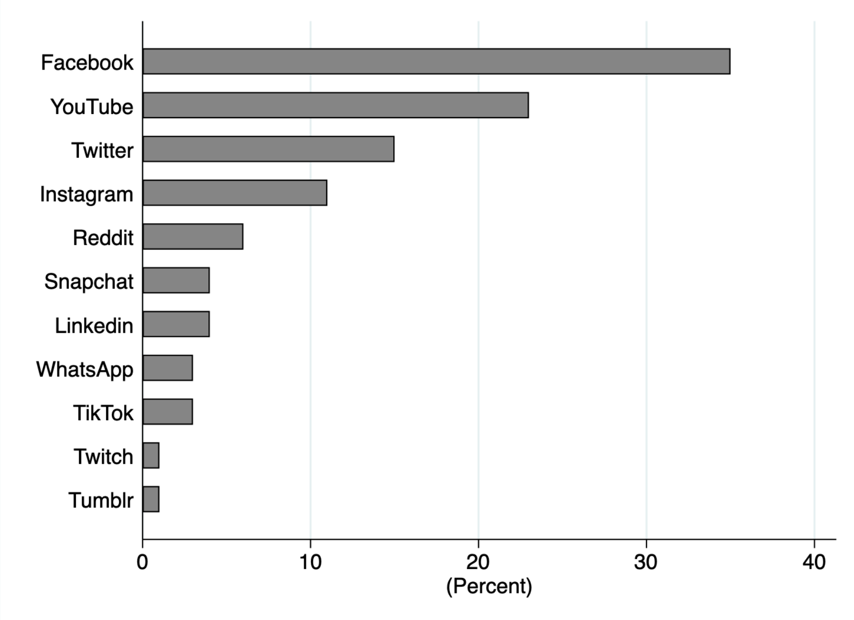


(a) Active Users

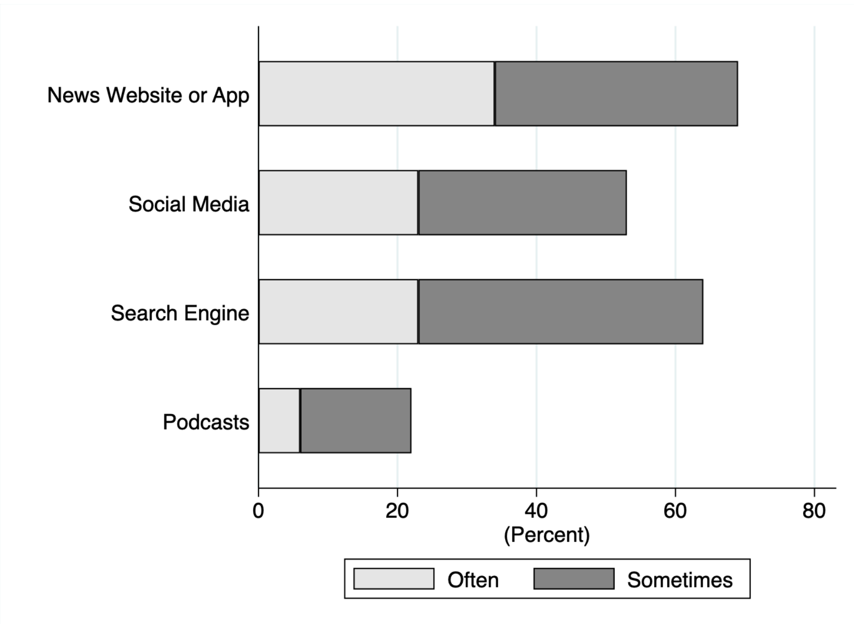


(b) Partisan Favorability

Figure 3.1: Social Media Usage (continued)



(c) Social Media News Sources



(d) Partisan Favorability

Source: Pew Research Center

https://www.pewresearch.org/journalism/2021/01/12/news-use-across-social-media-platforms-in-2020/ & https://www.pewresearch.org/fact-tank/2021/04/07/partisan-differences-in-social-media-use-show-up-for-some-platforms-but-not-facebook/

Hypothesis 3.1 *Conspiracy theorists are more likely to use fear and anger in their messaging than their peers elsewhere in the news media environment.*

This leads to three sub-hypotheses:

a Conspiracy theorists are more likely to use fear and anger in their social media posts than their peers elsewhere in the news media environment.

b Conspiracy theorists are more likely to use fear and anger in their news articles than their peers elsewhere in the news media environment.

c Conspiracy theorists are more likely to use fear and anger in their news headlines than their peers elsewhere in the news media environment.

The following section set out how the data is gathered, coded, and analysed. Then, the results are presented. Finally, the salient points raised by this chapter and discussed.

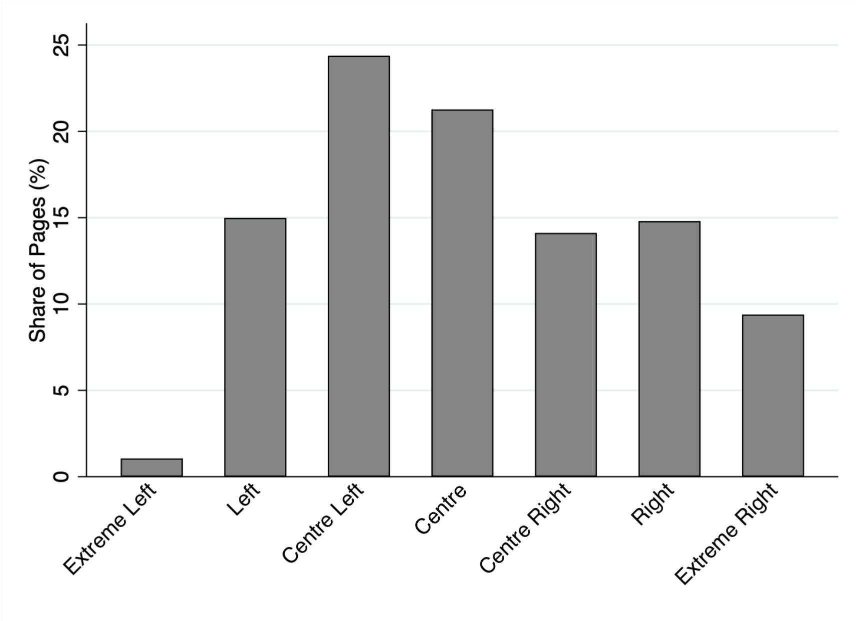
3.2 Data and Methodology

3.2.1 Data Sources

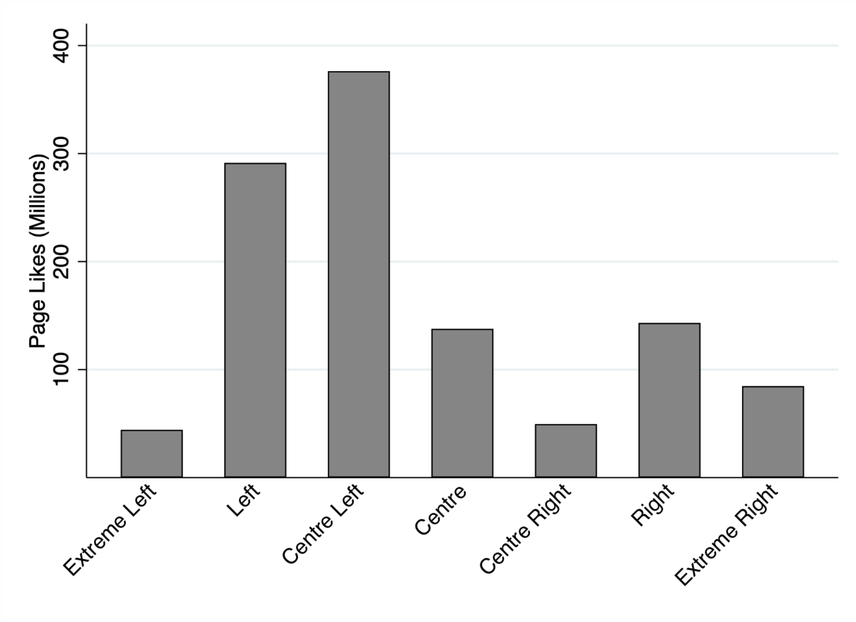
The chapter's research question - to what extent are news outlets that spread conspiracy theories more likely to use fear and anger in their messaging than their peers - a list of US-based news outlets was acquired from Media Bias/Fact Check (MBFC). This database contains information on over 3,800 news outlets globally. 2,461 of these outlets are located in the United States. Media Bias rates each news outlet across a range of measurements on political ideology and quality of reporting. These measurements include: 1) Left v Right Ideological Bias; 2) Factual Reporting; 3) Questionable Sources; 4) Conspiracy/Pseudoscience; 5) Traffic Estimates; 6) Credibility Rating; and 7) Pro-Science. News sites such as USA Today, Reuters Fact Check, Science Feedback, Washington Post, and NPR have used MBFC in the past. Further, Newsguard, another prominent fact-checking and media bias service rated MBFC as a credible source with a perfect score.[1] The data from MBFC was automatically downloaded using Python's Scapy package (Kouzis-Loukas 2016).

[1]MBFC can be accessed at: https://mediabiasfactcheck.com/

Figure 3.2: Overview of Facebook Data

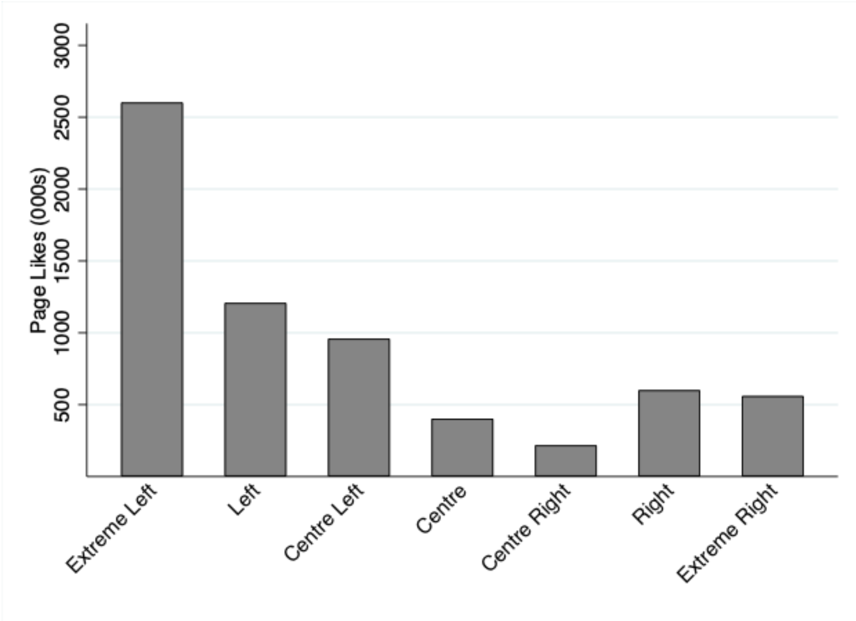


(a) Distribution of Pages by Ideology

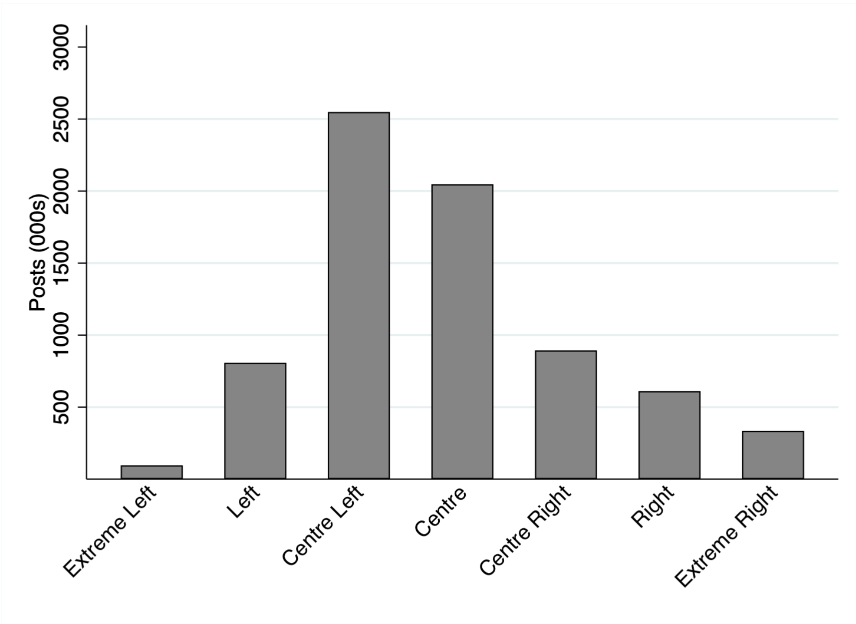


(b) Total Page Likes by Ideology

Figure 3.2: Overview of Facebook Data (continued)

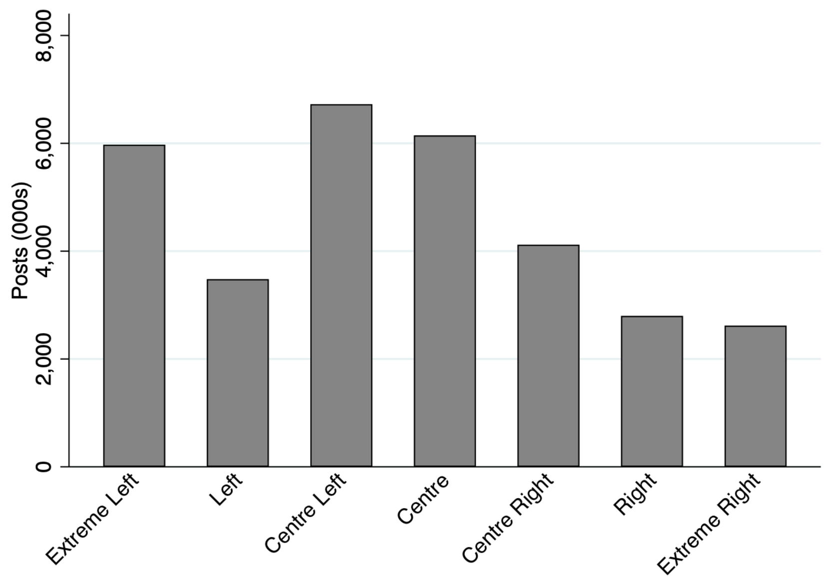


(c) Average Page Likes by Ideology

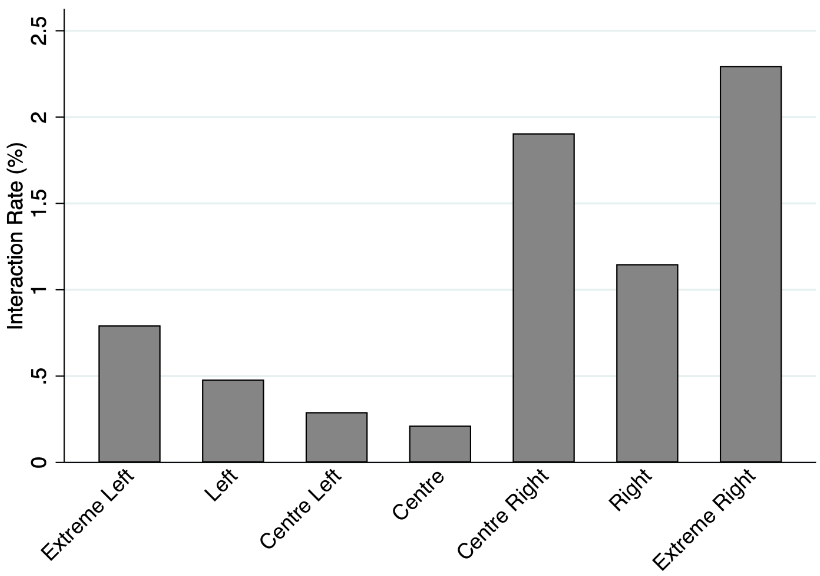


(d) Total Posts by Ideology

Figure 3.2: Overview of Facebook Data (continued)



(e) Average Posts by Ideology



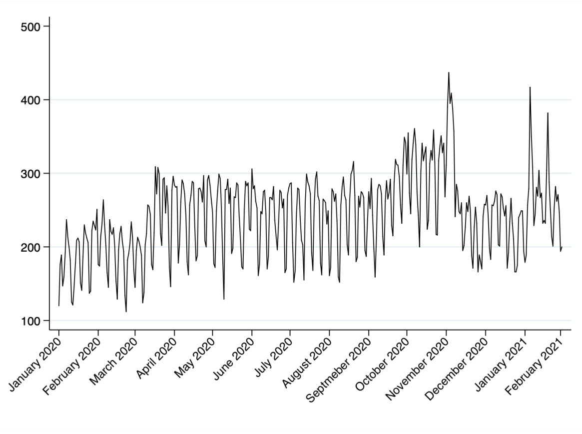
(f) Post Interaction Rate by Ideology

The second database used is Facebook's Crowdtangle platform (Crowdtangle). Crowdtangle returns data for every public post on the Facebook platform. This data includes the name of the page that created the post, the country that the page originated from, when the page was created, the date and time of the post, the text contained in the post, the type of post, the number of likes the page has at the time of the post, the number of followers the page has at the time of posting, and the total and type of interactions the post receives (CrowdTangle Team 2021).

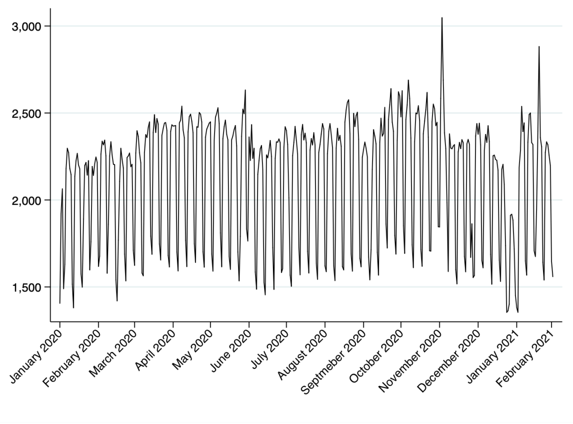
Using the news outlets surveyed by MBFC the Facebook domains of 1,744 US-based news outlets were identified. Using Crowdtangle's Historical Data Dashboard, all Facebook posts created by the 1,744 outlets were downloaded for the period 01 January 2020 to 31 January 2021. The justification for this time period was discussed in detail in Chapter 1. The time period was extended beyond 2020 to 31 January 2021 so as to include the post-election conspiracy theories, efforts to have the results of the election not certified, and the inauguration of Joe Biden as Donald Trump's successor in the office of the President. The dataset contains 7,221,509 posts from 1,608 unique Facebook pages.[2] This dataset downloaded from Crowdtangle was merged with the MBFC dataset. Each row of the news dataset contained the Facebook post level data as well as the MBFC information on the news outlet. This dataset effectively represents the population of Facebook posts from US-based news outlets for the time period 01 January 2020 to 20 January 2021. Figure 3.2 shows the distribution of pages, page likes, posts, and interaction rates across ideologies. Figure 3.3 shows the distribution of daily posts across the ideological spectrum.

[2]Some of the Facebook domains from the sites surveyed from MBFC were either discontinued or dormant.

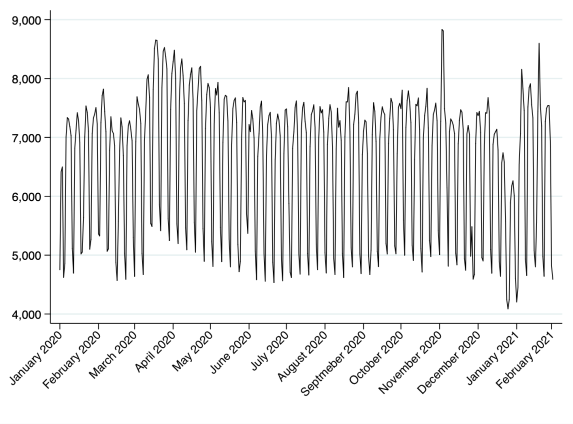
Figure 3.3: Posts per Day by Ideology



(a) Extreme Left

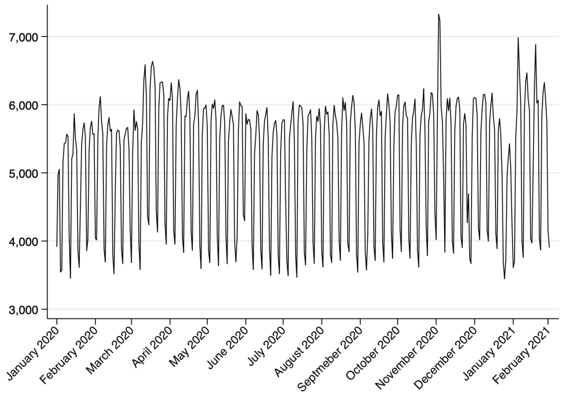


(b) Left

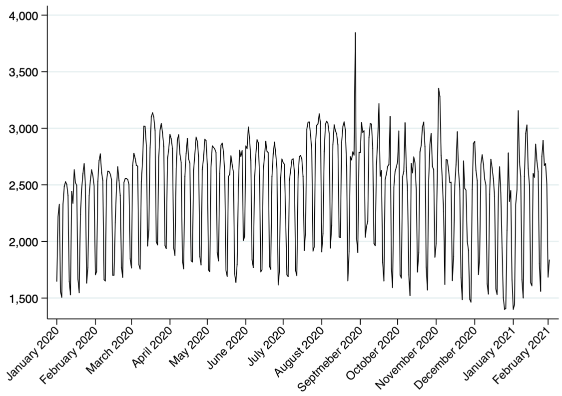


(c) Centre Left

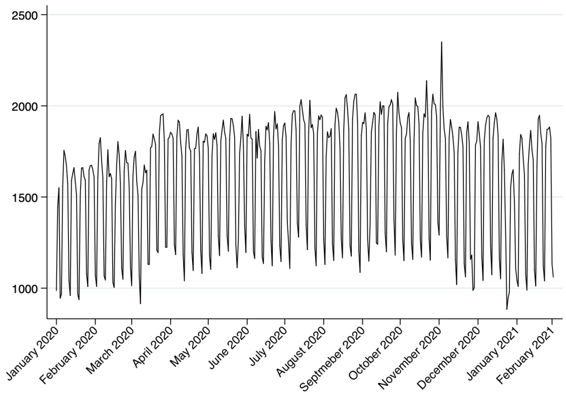
Figure 3.3: Posts per Day by Ideology (continued)



(d) Centre

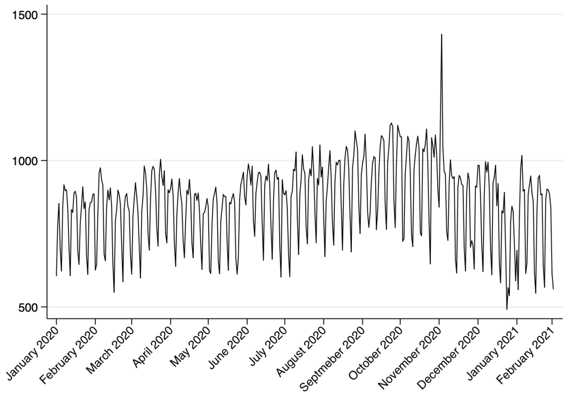


(e) Centre Right

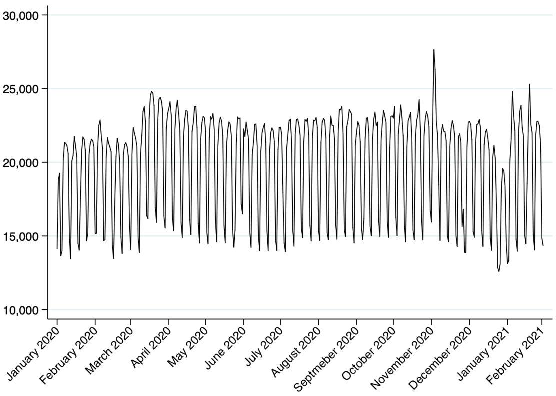


(f) Right

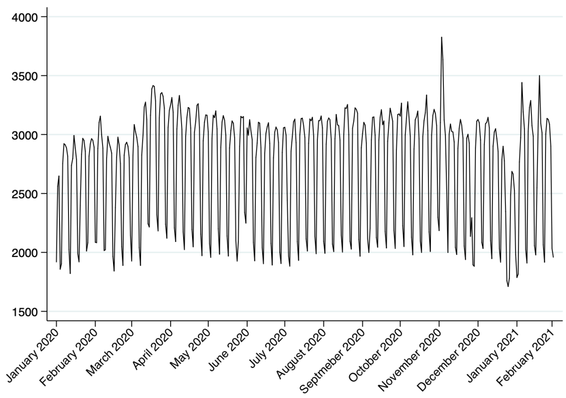
Figure 3.3: Posts per Day by Ideology (continued)



(g) Extreme Right



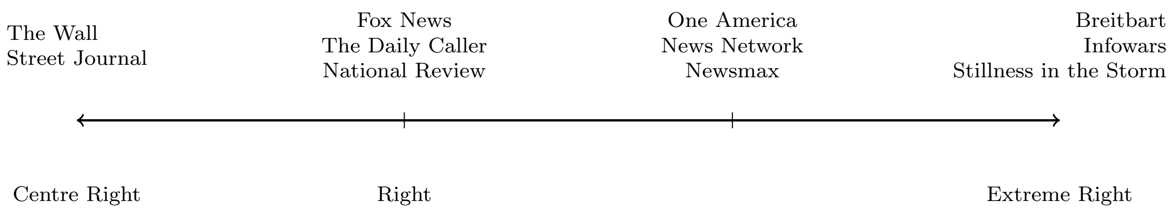
(h) Total Posts



(i) Mean Posts

The third dataset used was Webhose's API Archived Web Data (Webhose). This is a repository of content from news sites, reviews, blogs, and online discussions.[3] Using Boolean searches, Webhose returned news articles from nine US-based news sites. Namely, Breitbart.com, the Daily Caller, Fox News, Infowars, Newsmax, National Review, One America News Network, Stillness in the Storm, and The Wall Street Journal. These sites were chosen as they are ideologically proximate yet distinct. These outlets range from a broadsheet centre-tight news outlet (The Wall Street Journal) to extreme right propaganda sites (Infowars and Stillness in the Storm). Figure 3.4 demonstrates the ideological placements of each outlet.

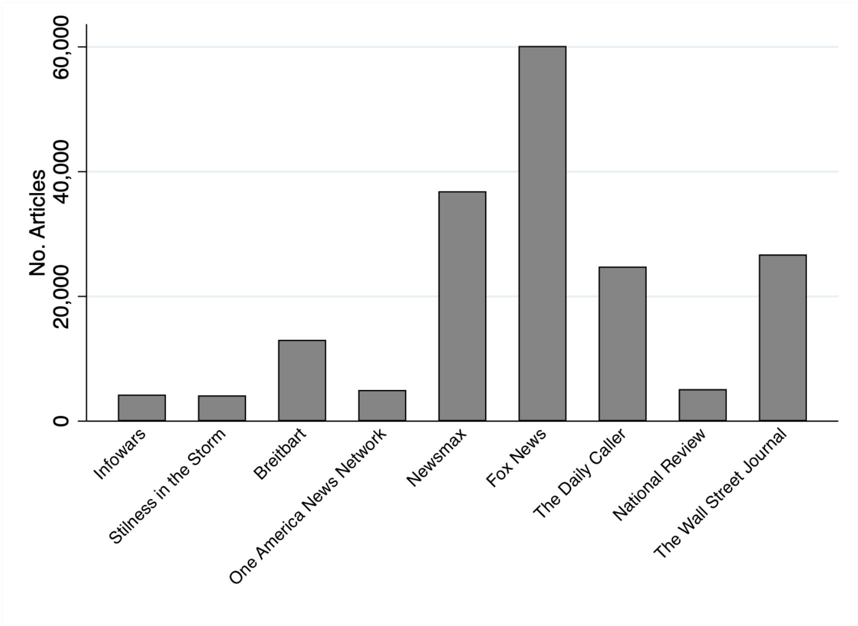
Figure 3.4: Examples of the ideological Placement of Selected News Organisations



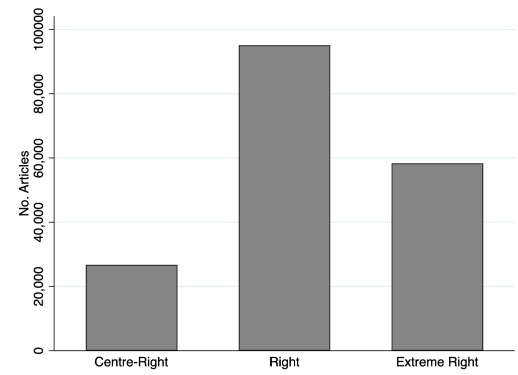
Articles from these outlets were collected for two periods: January 2020 to June 2020; and September 2020 to December 2020. This returned a total of 180,715 articles. July and August 2020 were excluded due to data collection limitations. Based on a Boolean search inputted in Webhose a dataset of every article that appeared on the nine news sources' websites during the two periods was returned. For each article, the dataset contained the article's text, the text of the article's headlines, and the date and time the article was posted. This dataset was merged with the MBFC dataset. Each row of the dataset contained the article level data as well as the MBFC information on the news outlet.

[3]The Webhose Data Archive can be accessed here: `https://webhose.io/`

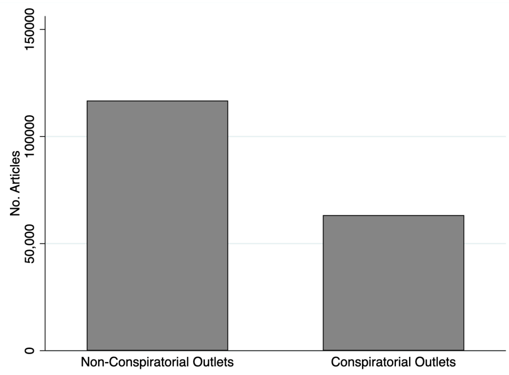
Figure 3.5: Overview of News Articles



(a) Articles by News Outlet



(b) Articles by Ideological Bias

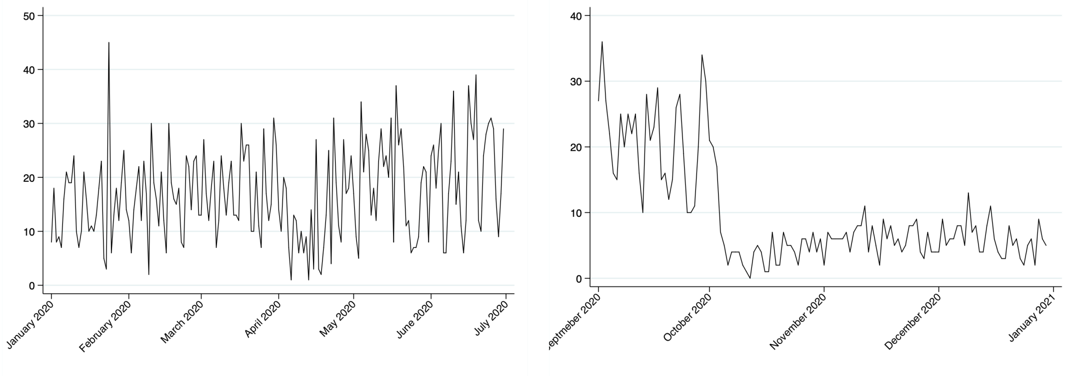


(c) Articles by Conspiratorial Outlets

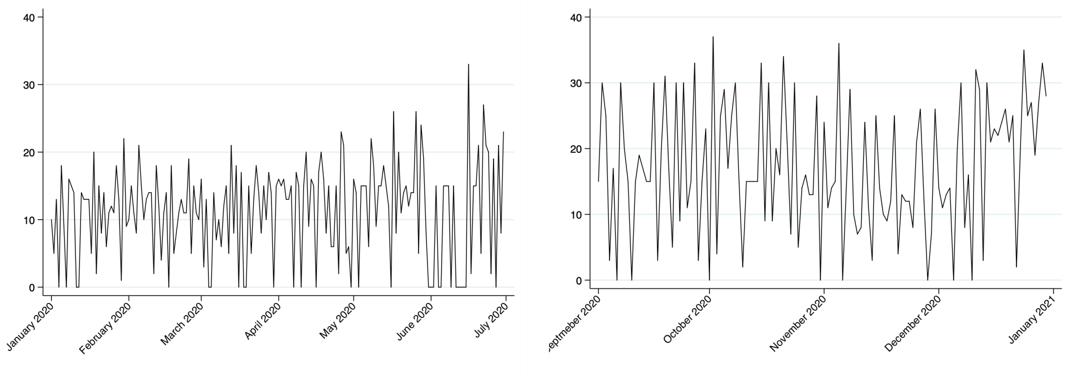
This dataset represents the population of articles from the nine news outlets for the time period 01 January 2020 to 30 June 2020 and 01 September to 31 December 2020. Figures 3.5 and 3.6 demonstrate the distribution of articles across sites, ideological bias, conspiratorial outlook, and time.

Only nine news sources were chosen because of computing and funding limitations. However, these nine sources represent the breath of right-wing news coverage in the United States. Ranging from the centre-right broadsheet, the Wall Street Journal to the extreme-right Infowars. Figure 3.5 demonstrates the ideological distribution of the news sites. The focus on right-wing outlets was for two reasons. First, according to MBFC, there is a preponderance of conspiratorial sites is on the right of the US news media environment. Second, focusing on a more ideological homogeneous sample reduced any variation caused by ideological distance. The full population of 2020 articles from these sites was not downloaded due to funding constraints. However, the two periods cover the Covid-19 and 2020 US Presidential Elections well. Therefore, there is no reason to believe that the two missing months (July and August 2020) should have any material impact upon findings.

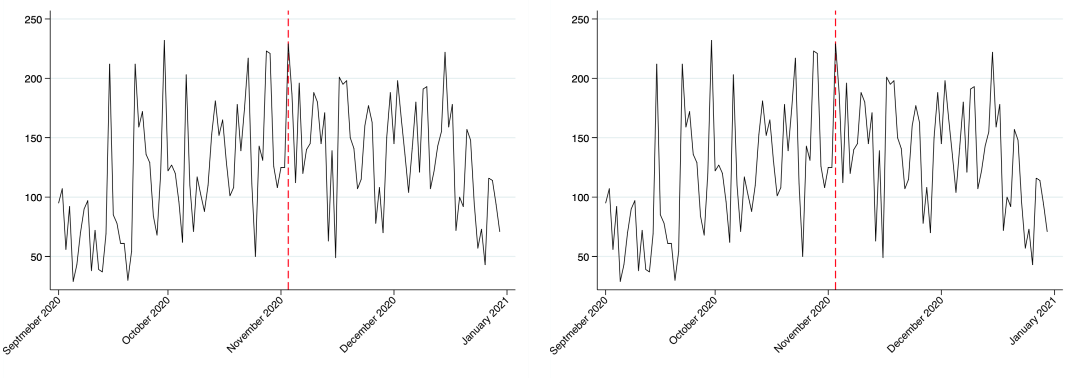
Figure 3.6: Articles Posted per Day



(a) Infowars

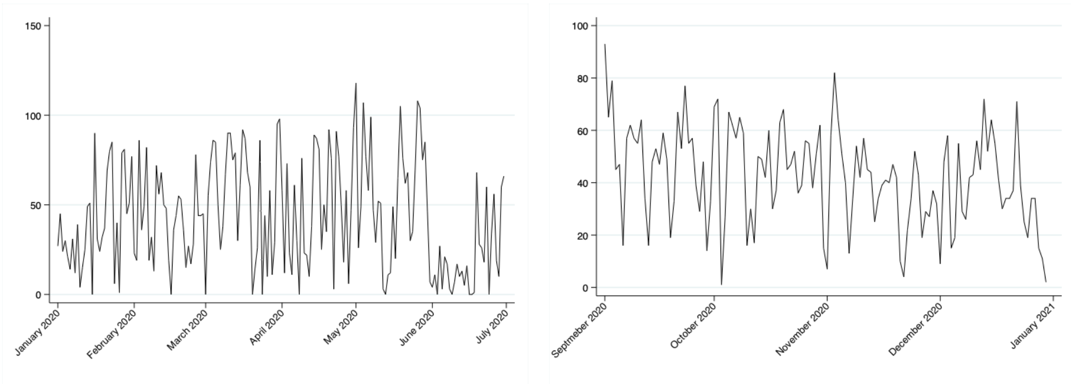


(b) Stillness in the Storm

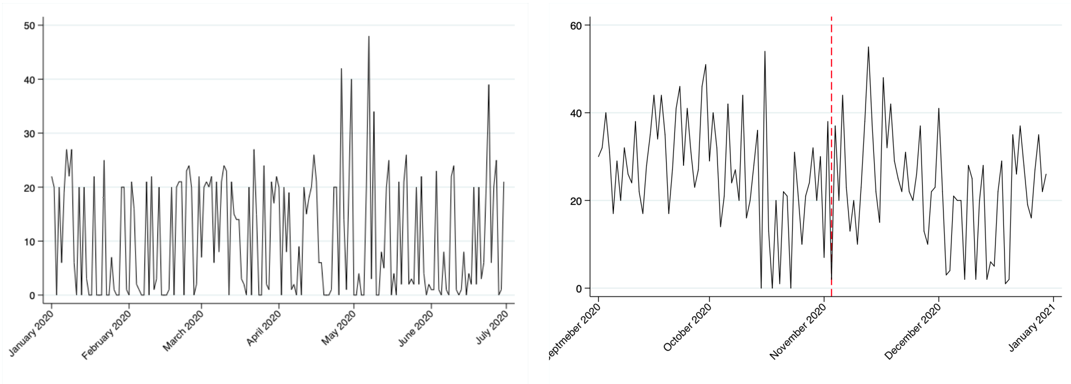


(c) Breitbart

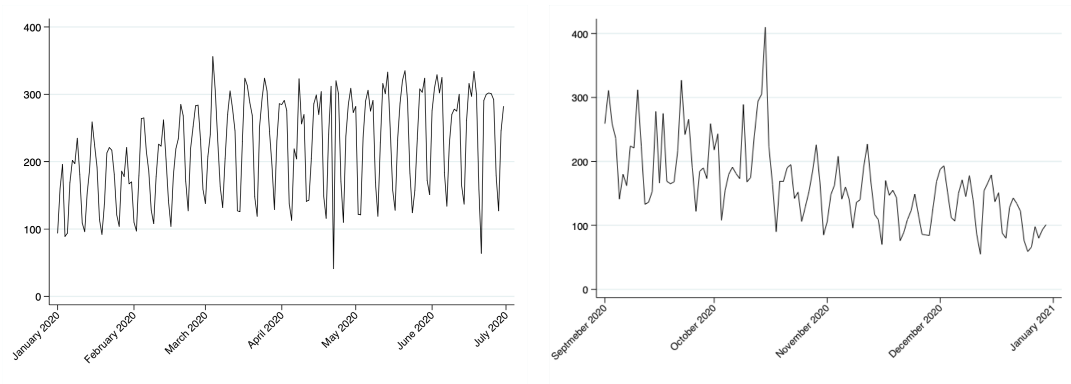
Figure 3.6: Articles Posted per Day (continued)



(d) One America News Network

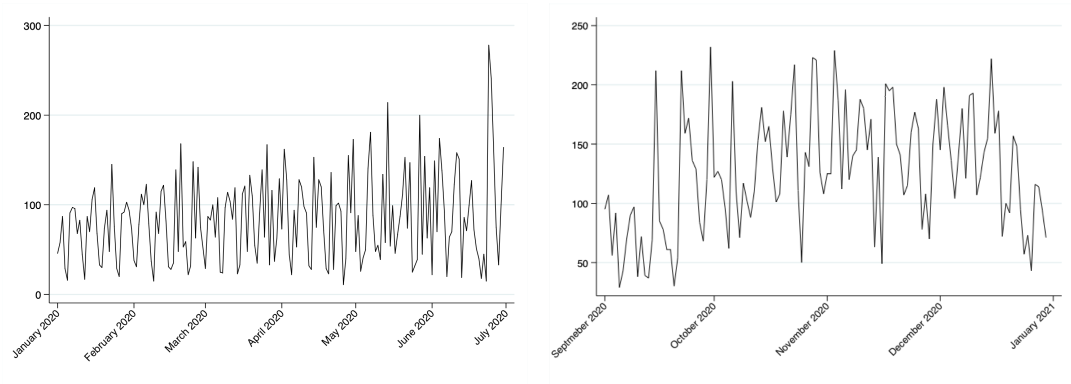


(e) News Max

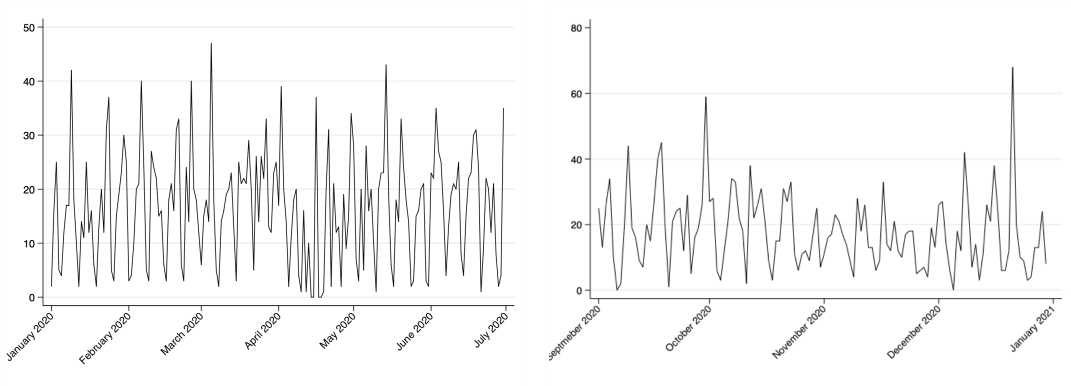


(f) Fox News

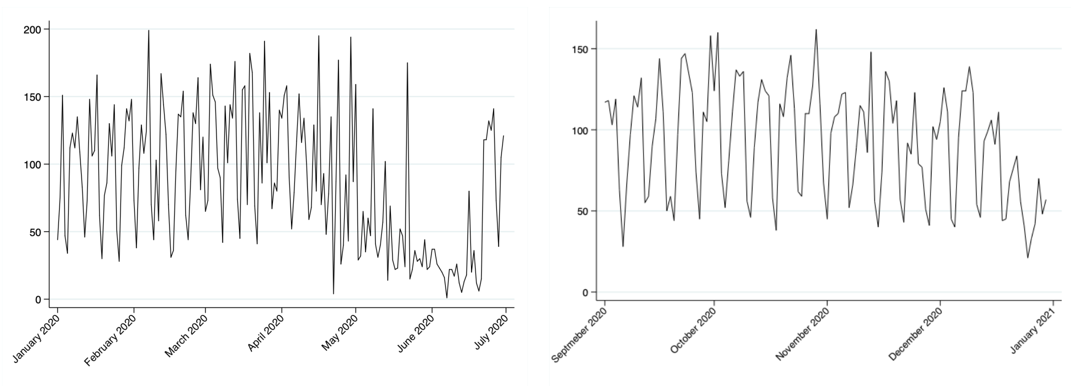
Figure 3.6: Articles Posted per Day (continued)



(g) The Daily Caller

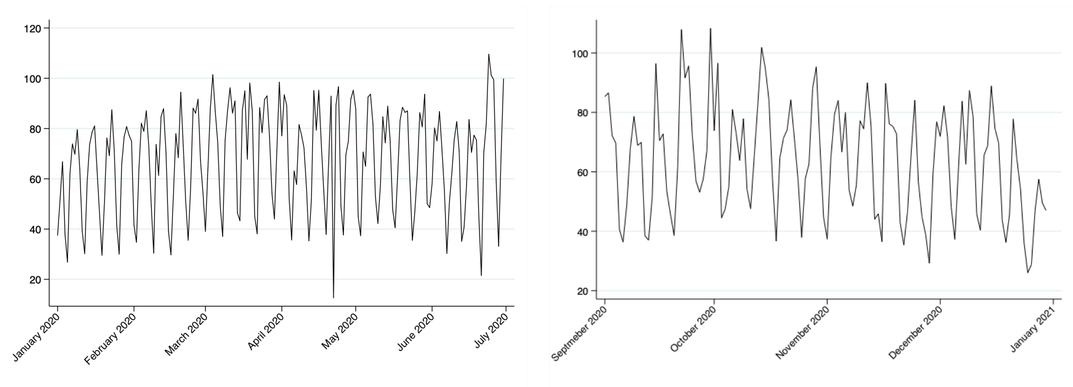


(h) National Review

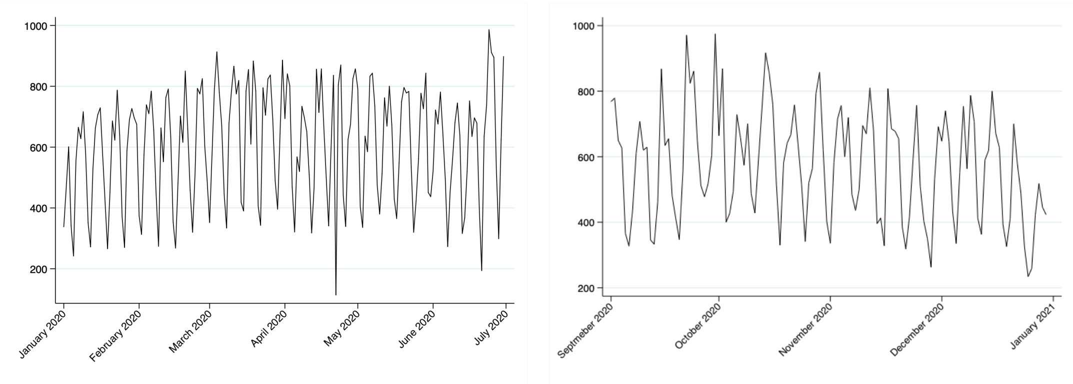


(i) The Wall Street Journal

Figure 3.6: Articles Posted per Day (continued)



(j) Mean



(k) Total

3.2.2 Text Data Preprocessing

Several of the variables used in this chapter are derived from text, known as text as data. With both an ever increasing share of human interactions recorded as digital text and new technologies and computing power becoming available, text as data and its analysis has greatly increased in popularity within the social sciences (Gentzkow, Kelly & Taddy 2019). This has allowed for the systematic analysis of large scale text collections such as the text variables within the Facebook and article/headline datasets (Grimmer & Stewart 2013). In order to analysis such data a number of pre processing steps must be undertaken in order to 'clean' the text. The first step is to remove words and characters that would interfere with any analysis. For example, stop words. Stop words are a set of commonly used words in any language. For example, in English words such as 'a' 'the', 'is', and 'are' are stop words. These words are eliminated as they are commonly used by infer little useful information (Wilbur & Sirotkin 1992). All stop words as well as punctuation, symbols, numbers, twitter characters, URLs, digits, and hyphens were removed from the text variables within both datasets. Furthermore. rare words are removed. In this instance, words that appeared less than five times in less than three documents were removed. Again, these did not confer meaningful information so were eliminated. In cleaning the data in this manner a more meaningful analysis of the text can take place.

3.2.3 Dependent Variable - The Sentiment of Facebook Posts, News Articles, and News Headlines

The dependent variable for this study is the level of fear and anger present in each Facebook post, news article, or news headline. In particular, this chapter is interested in the presence of words that connote fear and anger. To measure the level of these emotions in each post a dictionary approach is used. Using the tidytext package in R the number of words that represent fear and anger in each post were identified (Silge & Robinson 2016). This was done using the National Research Council Canada Emotion Lexicon (NRC). The NRC is a list of English words and their associations with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive). These were manually coded using crowdsourcing and has been shown to perform well vis-a-vis other methods of annotating the emotions within text (Mohammad & Turney 2010, Mohammad & Turney 2013). Tidytext uses a simple bag of words dictionary approach where the number of words that that denotes anger are counted. This chapter uses the proportion of words in a given post, article, or headline that denote fear or anger. These proportions are returned through the following formulae:

$$(1)\ fear = \frac{\sum fear\, words}{\sum words\, in\, text}\, x\, 100$$

$$(2)\ anger = \frac{\sum anger\, words}{\sum words\, in\, text}\, x\, 100$$

3.2.4 Independent Variables

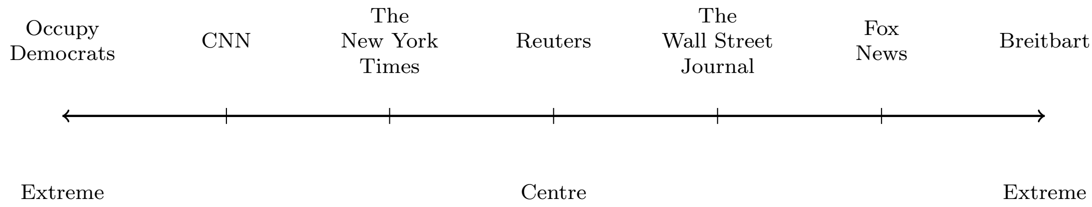
Conspiratorial News Outlets

MBFC identifies whether or not a news outlet can be designated as a conspiracy site. Such sites publish news articles on unverifiable conspiracy theories such as the New World Order, the Illuminati, False Flags, Aliens anti-vaccination propaganda, and so on. Many of these sites also peddle pseudoscience. Pseudoscience initially comes across as harmless. For instance, the belief in astrology. However, pseudoscience is highly relayed to conspiracy theories. For instance, climate change denialism and Holocaust denialism, are both highly charged conspiracy theories that overlap with pseudoscience. This chapter utilises the MBFC conspiratorial news outlets as tto demonstrate that conspiracy theorists use higher levels of fear and language in media outlets' messaging.

Ideological Bias

MBFC uses a combination of objective and subjective measurements when determining the ideological bias of news outlets. When determining the ideological bias of a news source there is no truly objective method. Further, the ideological bias of news sources is contextual. For example, many centre-left news outlets in the United States would be considered centre-right in Europe. Indeed, right-wing sources may be considered far or extreme-right in Europe. Despite the inherent subjectivity of rating the ideological bias of news sources MBFC does use a standardised methodology that reduces the random error introduced by the subjective nature of the measurement. MBFC uses sixteen political salient policy areas to evaluate the bias of a source. These are: General Philosophy; Abortion; Economic Policy; Education Policy; Environmental Policy; Gay Rights; Gun Rights; Health Care; Immigration; Military; Personal Responsibility; Regulation; Social Views; Taxes; Voter ID; and Worker's/Business Rights. Sources rated on either the left or right tend to favour most of the policies in their respective categories. The further to the extreme the more likely this is to become full agreement with these positions. Further, the more extreme the position the more likely there is to be propaganda and factually incorrect reporting in their articles. A centre-left or centre-right source will favour more but not all from one side. A Centre site tends to be more balanced, provide perspectives from both sides, and have limited editorial positions. Figure 3.7 shows the MBFC ideological placements for some well-known US news organisations.

Figure 3.7: Examples of the ideological Placement of Well-Knows US News Organisations



Standard of Reporting

Each source provided by MBFC has a “Factual Reporting” rating based on the standard or the sources they use. There are six categories for this score: Very High; High; Mostly Factual; Mixed; Low; Very Low. A rating of “Very High Factual Reporting” means that the source is always factual, cites credible information,.and quickly makes corrections to incorrect information. Further, the site will have never failed a fact check in either its news reporting or op-eds. Very low means the source rarely uses credible sources and is in no way trustworthy for reliable reporting. The articles on these sites always need to be fact-checked for fake news, conspiracy theories, and propaganda. While ratings the sites MBFC pays particular to the following signals of bias; Bias by Omission; Bias by labelling (for example, describing those who are ideologically proximate to the outlet in a positive manner); Bias by Placement; Bias by Selection of Sources; Bias by Story Selection; Confirmation Bias; Connotation; Denotation; Loaded Language; Purr Words; and Snarl Words. Other factors that are monitored include whether the headline and text of the article match, whether important stories are featured prominently, and are alternative points of view offered.

Topics

When analysing whether or not conspiracy theorists utilise heightened levels of negative emotive language it is important to control for the subject matter of the article or post. While some sites such as Infowars may be almost exclusively political many other sites, including many conspiratorial sites, report on a wide range of topics. For example, Breitbart.com is a news outlet that engages in conspiratorial rhetoric. However, Breitbart reports on a wide range of topics, including sports, entertainment, and technology. Of course, While politics and conspiracy theories can bleed into these topics. For instance, Colin Kaepernick's taking the knee, Megan Rapinoe's outspoke advocacy for social justice, and the widespread conspiracy theories about Hollywood and paedophile rings. However, there is no theoretical reason to anticipate Breitbart's reporting on a regular-season NFL game to vary in terms of its use of fear and anger vis-a-vis the New York Times simply because the site peddles conspiracy theories.

To this end, Latent Dirichlet Allocation (LDA Topic Modelling) enables researchers to control for the topic(s) contained in a text. LDA topic models are computer algorithms that identify latent patterns of word occurrences using the distribution of words in documents across a corpus of documents (Jacobi, Van Atteveldt & Welbers 2016). Using the Quanteda package in R clusters of words that co-occur in the two corpora in this study into 25 topics (Benoit, Watanabe, Wang, Nulty, Obeng, Müller & Matsuo 2018). That is, articles and Facebook posts are given a score for each topic bases on the co-occurrence of the words in each text across the entire corpus. The headlines and articles dataset used the same topics derived from the articles as they give a better indication as to what the article and associated headline is discussing. Please note two junk topics in te Facebook dataset and one junk topic in the news article/headline dataset were excluded from the analysis. Further, two topics from the article/headline dataset were combined as they were related to the same topic. The full list of topics, their labels, and their most probable tokens for both datasets can be seen in Appendix B.2

Before any analysis can take place these need to be a) manually labelled and b) manually checked for validity (Hagen 2018). The first step is intuitive. The topics are a series of scores. A human must investigate each topic and label it accordingly. This ties into the second step. Initially, the most popular words in each topic are investigated to gauge what the topic relates to. Next, the top 500 Facebook posts and news articles for each topic were read to gauge the nature of each topic. Sometimes there are 'junk' topics returned. These are topics that have co-occurrent words but there is no theme across the articles that rate highly on this topic. Such junk topics are excluded from the analysis. The Facebook dataset contained two junk topics while the article/headline dataset contained one junk topic. These topics were excluded. Furthermore, the article/headline dataset contained two topics whose content across articles rating highly in the topics were almost identical. These topics were combined.

3.2.5 Empirical Strategy

This paper investigates whether conspiratorial news outlets use a higher proportion of fear and anger words using three independent variables. There are the proportion of fear and anger words in i) Facebook posts, ii) news articles and iii) news headlines. The chapter employs an ordinary least squares (OLS) model with standard errors clustered as the level of the news outlet and controls for the ideological bias and reporting standard of the news outlet as well as the topic being discussed in the particular post or news article.

The regression equations are as follows:

1. Facebook posts:

(a) $Y_{fear} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

(b) $Y_{anger} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

2. News Articles

(a) $Y_{fear} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

(b) $Y_{anger} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

3. News Headlines:

(a) $Y_{fear} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

(b) $Y_{anger} = \beta_0 + \beta_1 Conspiratorial\ Outlets + \beta_2 Ideological\ Bias + \beta_3 Standard\ of\ Reporting + \beta_{4-27} LDA\ \ Topics + \epsilon$

3.3 Results

Do conspiratorial news outlets, all else equal, use heightened levels of fear and anger in their messaging than their non-conspiratorial peers? This section presents the results of the chapter's investigation. First, the results for the analysis on Facebook posts is presented. Subsequently, the analysis of news articles is presented. Finally, the results of the analysis of news headlines is presented.

3.3.1 Facebook Posts

Do conspiratorial news outlets used heightened levels of fear and anger in their Facebook posts? As Table 3.1 and Figure 3.8 demonstrate, conspiratorial outlets do, on average, use heightened levels of both emotions in their Facebook posts.

In terms of fear, conspiratorial outlets (M= 8.93, SD= 11.5) when compared with non conspiratorial outlets (M= 8.25 SD= 11.84) are statistically significantly more likely to use fear in their Facebook posts $t(756{,}853) = -44.49$, $p = .0000$.

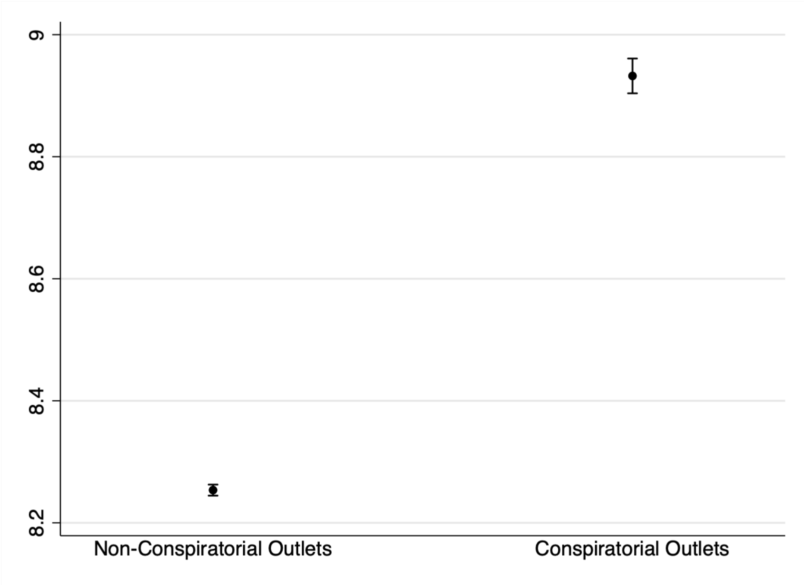
In terms of anger, conspiratorial outlets (M= 6.2, SD= 9.19) when compared with non conspiratorial outlets (M= 5.44 SD= 8.87) are also statistically significantly more likely to use anger in their Facebook posts $t(740{,}704) = -62.78$, $p = .0000$.

Therefore, upon initial inspection, conspiratorial outlets do indeed utilise heightened levels of fear and anger in their Facebook posts.

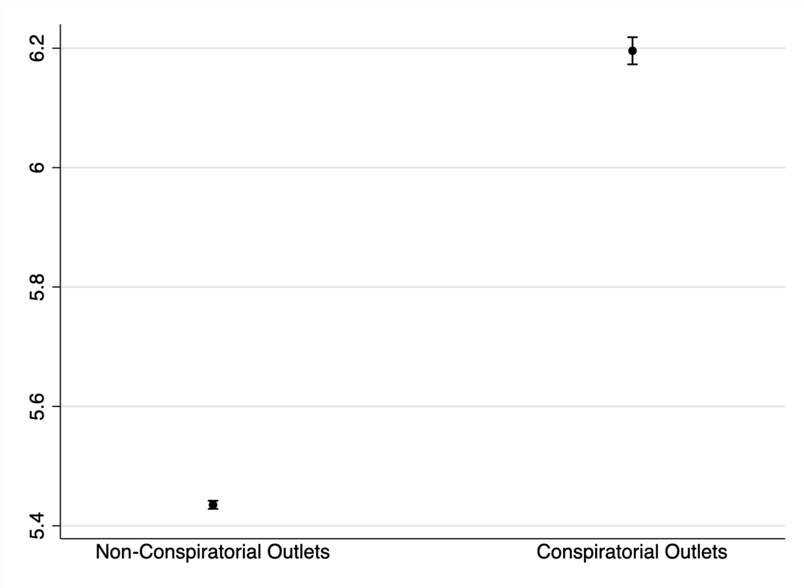
Table 3.1: Facebook Dependent Variables Summary Statistics

			Fear		
Variable	**N**	**Mean**	**St.Dev**	**Minimum**	**Maximum**
Conspiratorial News Outlets	625,622	8.93	11.5	0	100
Non-Conspiratorial News Outlets	6,595,887	8.25	11.84	0	100
			Anger		
Variable	**N**	**Mean**	**St.Dev**	**Minimum**	**Maximum**
Conspiratorial News Outlets	625,622	6.2	9.19	0	100
Non-Conspiratorial News Outlets	6,595,887	5.44	8.87	0	100

Figure 3.8: Facebook Posts Dependent Variables Confidence Intervals



(a) Fear



(b) Anger

Does this relationship hold when controlling for the confounding variables outlined in the previous section? As table 3.2 demonstrates both fear and anger in the OLS results are positive and statistically significant. Therefore, conspiracy theorists do indeed use heightened levels of anger and fear in their Facebook posts.

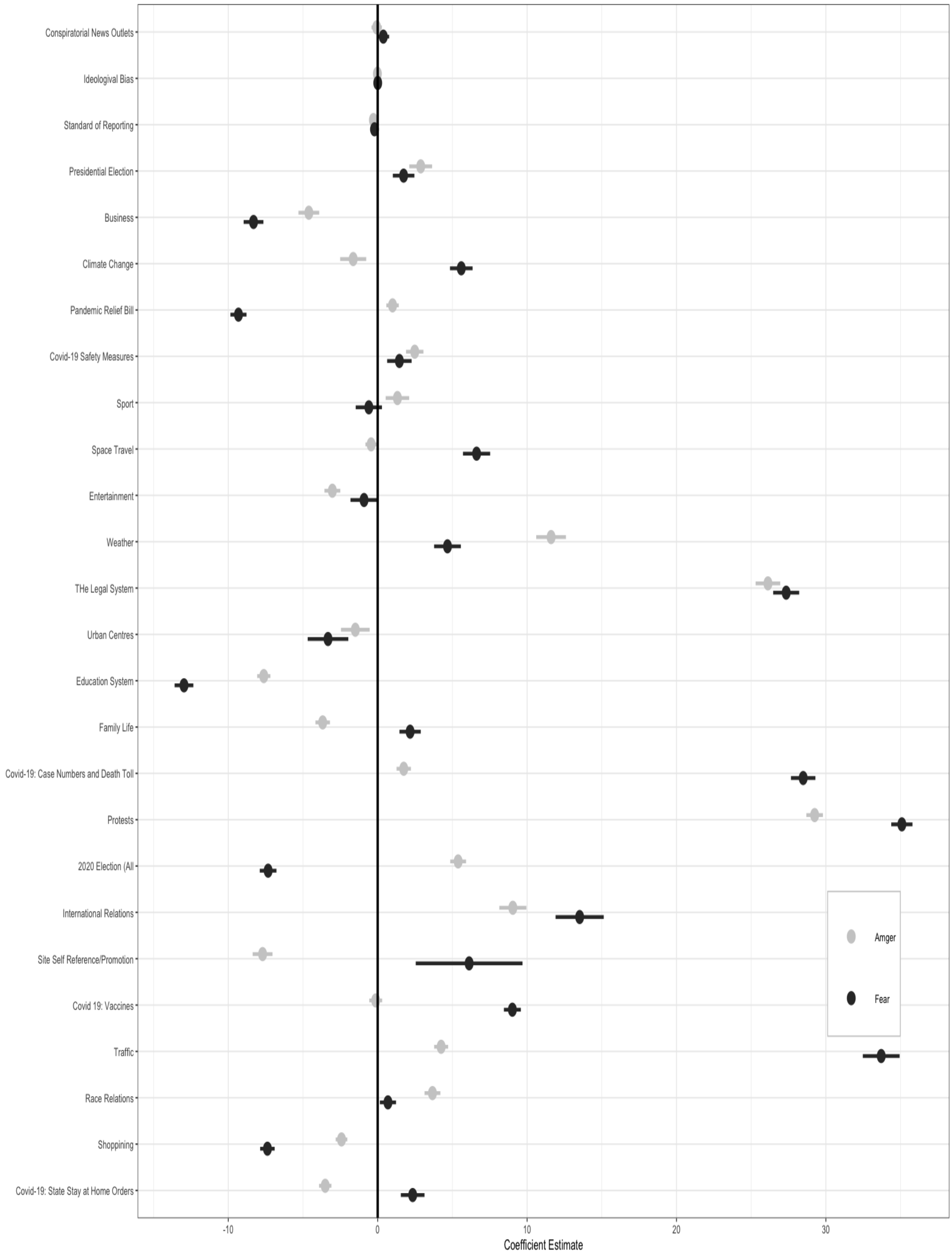
Figure 3.9 shows the coefficient plots for the fear and anger OLS regression results. This figure demonstrates that while positive and statistically significant, the fact that the site is conspiratorial or not does not have the largest impact on the use of fear and anger. Topics such as the legal system, and Covid-19 cases totals and death tolls, protests, and interestingly, traffic all have large effects on the presence of either fear and anger in Facebook posts. This is to be expected. These are all either highly contentious topics and/or naturally emotive topics. For example, it is unsurprising that posts discussing protests and civil unrest or the death toll from Covid-19 have heightened fear and anger compared to posts discussing sport, family life, or sites' self-promotion. Part of the effect size of these topics vid-a-vis fear and anger this is to do with the measurement of the variables. Fear and anger have a minimum of zero and a maximum of 100 while the topics range from 0 to 1.

Table 3.2: Facebook Posts OLS Regression Results

	Fear	**Anger**
Conspiratorial Sites	0.377	0.067
	(0.000)	(0.000)
Ideological Bias	0.003	−0.020
	(0.931)	(0.466)
Standard of Reporting	−0.213	−0.289
	(0.000)	(0.000)

Note: p-values in parentheses

Figure 3.9: Facebook Coefficient Plots



3.3.2 News Articles

Do conspiratorial news outlets used heightened levels of fear and anger in their news articles? As Table 3.3 and Figure 3.10 demonstrate, conspiratorial outlets, on average, use lower levels of both emotions in the articles they post on their websites.

In terms of fear, conspiratorial outlets (M= 1.56, SD= 1.38) when compared with non conspiratorial outlets (M= 2.93 SD= 3.32) are statistically significantly less likely to use fear in their news articles t(162,011) = -9.7179, p = .0000.

In terms of anger, conspiratorial outlets (M= 1.28, SD= 1.18) when compared with non conspiratorial outlets (M= 1.29 SD= 1.67) are statistically significantly no more or less likely to use anger in their news articles t(160,617) = -62.78, p = .0000.

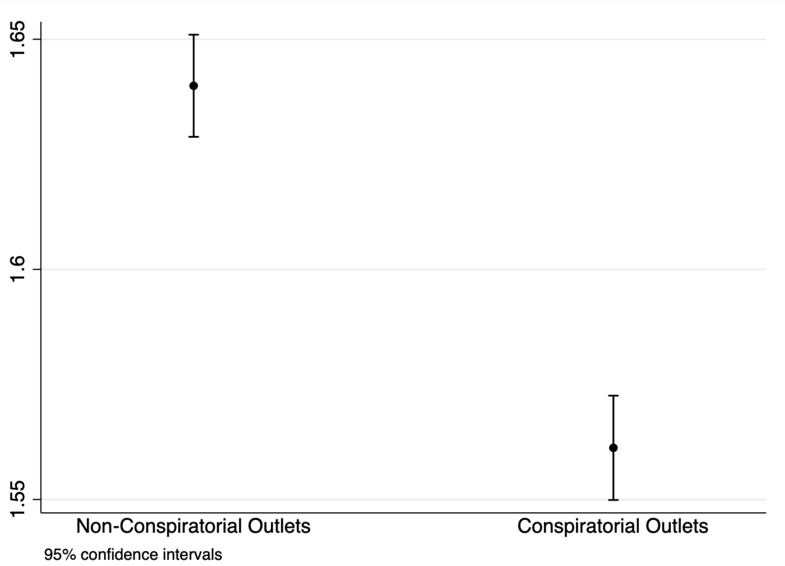
Therefore, upon initial inspection, conspiratorial outlets actually utilise lower levels of fear in their news articles when compared to their non-conspiratorial peers while demonstrating no difference in their use of anger.

Table 3.3: News Article Dependent Variables Summary Statistics

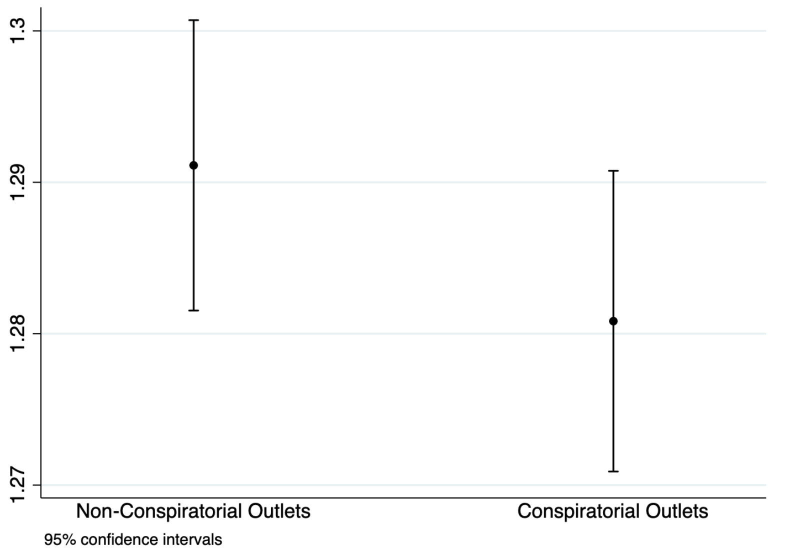
Fear					
Variable	**N**	**Mean**	**St.Dev**	**Minimum**	**Maximum**
Conspiratorial News Outlets	63,284	1.56	1.38	0	50
Non-Conspiratorial News Outlets	116,774	2.93	3.32	0	62.5

Anger					
Variable	**N**	**Mean**	**St.Dev**	**Minimum**	**Maximum**
Conspiratorial News Outlets	63,288	1.28	1.18	0	100
Non-Conspiratorial News Outlets	116,774	1.29	1.67	0	37.5

Figure 3.10: Facebook Posts Dependent Variables Confidence Intervals



(a) Fear



(b) Anger

Does this relationship hold when controlling for the confounding variables outlined in the previous section? As table 3.4 demonstrates both fear and anger in the OLS results are negative. However, they are not statistically significant. Therefore, there is no evidence that conspiratorial news outlets use any more or less fear and anger in their news articles than their non-conspiratorial peers.

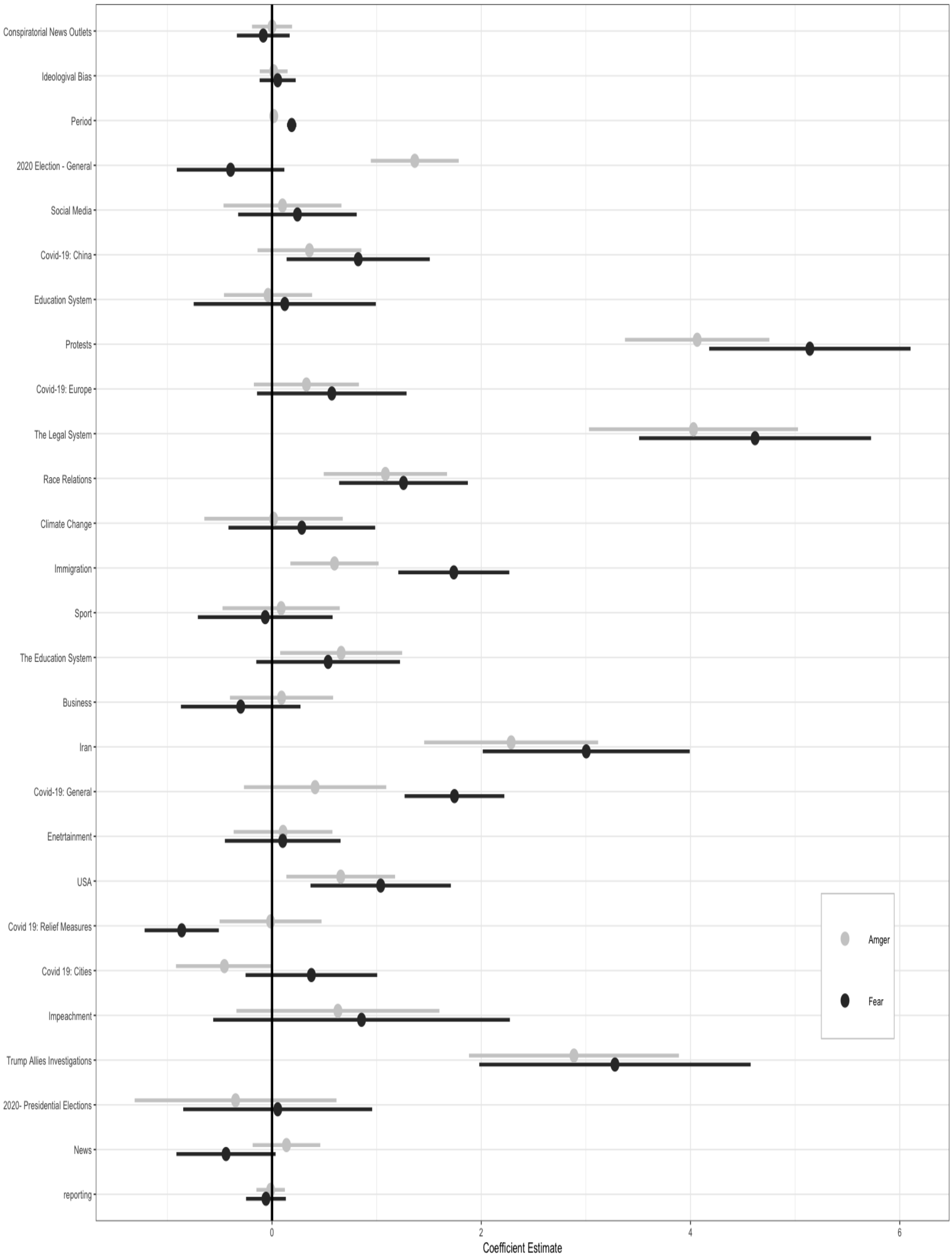
Figure 3.11 shows the coefficient plots for the fear and anger OLS regression results. This figure demonstrates that topics such as climate change, Iran, and local news events all have large effects on the presence of fear and anger in Facebook posts. Climate change and Iran are politically contentious issues and heightened emotion may be expected. Interestingly, articles relating to America have heightened levels of fear but lower levels of anger. This may be due to the right-wing ideological bias of the sample. Again, these effect sizes are influenced by the measurement of the variables.

Table 3.4: News Articles Regression Results

	Fear	**Anger**
Conspiratorial Sites	−0.128	−0.004
	(0.339)	(0.970)
Ideological Bias	0.081	0.018
	(0.386)	(0.786)
Standard of Reporting	−0.087	−0.015
	(0.381)	(0.821)

Note: p-values in parentheses

Figure 3.11: Articles Coefficient Plots



h

3.3.3 News Headlines

Do conspiratorial news outlets used heightened levels of fear and anger in their news headlines? As Table 3.5 and Figure 3.12 demonstrate conspiratorial outlets do, on average, use heightened levels of both emotions in their news headlines.

In terms of fear, conspiratorial outlets (M= 3.73, SD= 5.98) when compared with non conspiratorial outlets (M= 3.11 SD= 5.42) are statistically significantly more likely to use fear in their Facebook posts t(119,230) = -21.635, p = .0000.

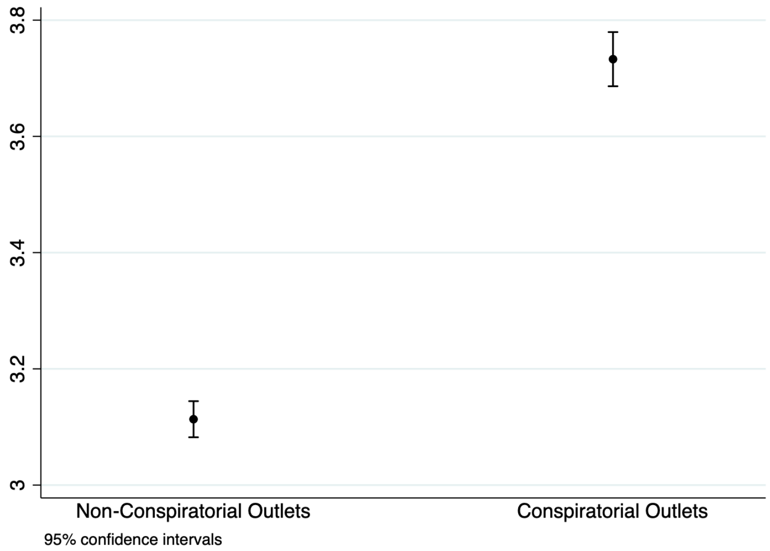
In terms of anger, conspiratorial outlets (M= 2.95, SD= 5.23) when compared with non conspiratorial outlets (M= 2.42 SD= 4.74) are also statistically significantly more likely to use anger in their Facebook posts t(119,408) = -21.328, p = .0000.

Therefore, upon initial inspection, conspiratorial outlets do indeed utilise heightened levels of fear and anger in their news headlines.

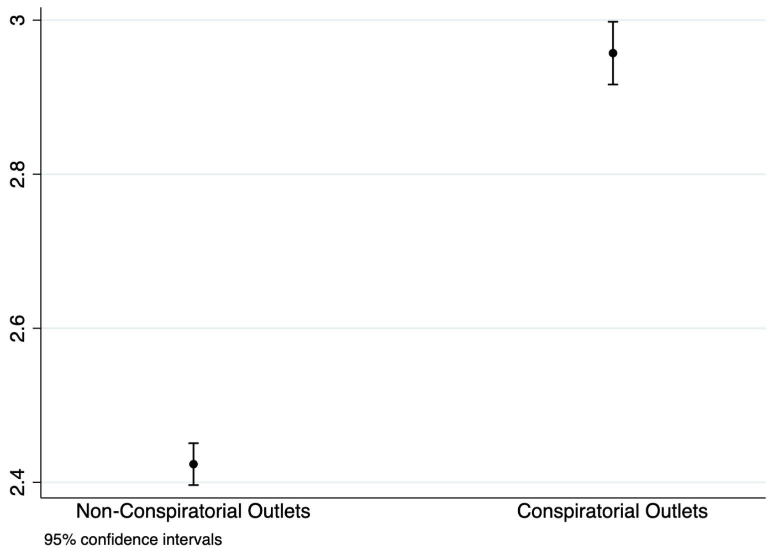
Table 3.5: News Headlines Dependent Variables Summary Statistics

	N	**Mean**	**St.Dev**	**Minimum**	**Maximum**
Fear					
Conspiratorial News Outlets	63,288	3.73	5.98	0	60
Non-Conspiratorial News Outlets	116,788	3.11	5.42	0	67
Anger					
Conspiratorial News Outlets	63,288	2.95	5.23	0	50
Non-Conspiratorial News Outlets	116,788	2.42	4.74	0	50

Figure 3.12: News Headlines Confidence Intervals



(a) Fear



(b) Anger

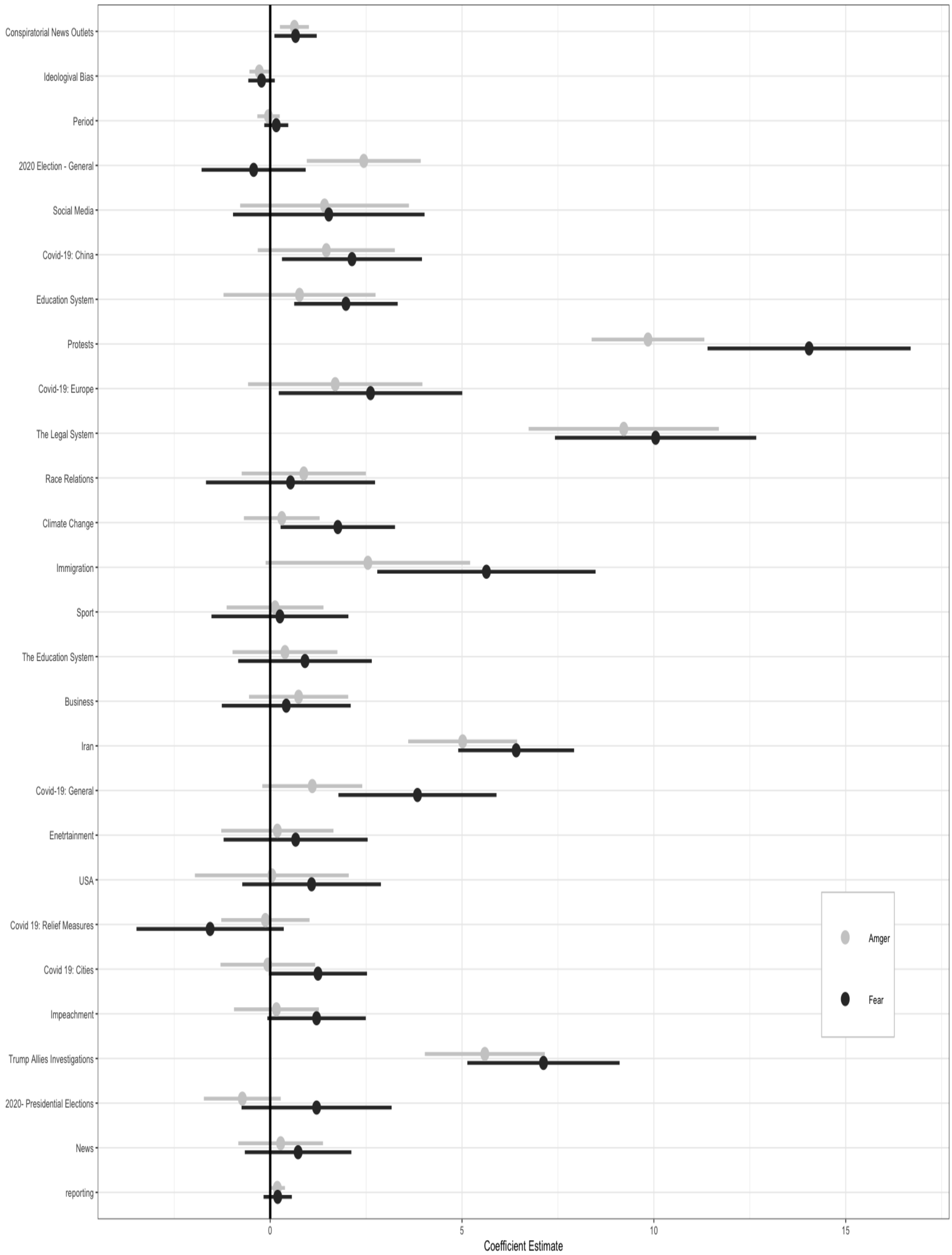
Figure 3.14 shows the coefficient plots for the news headlines fear and anger OLS regression results. This figure demonstrates that while positive and statistically significant, the fact that the site is conspiratorial or not does not have the largest impact on the use of fear and anger. Topics such as federal court cases, protests and civil unrest, Iran, and the investigations into Donald Trump and his close allies all have large effects on the presence of fear and anger in news headlines. These are all highly contentious topics and it is perhaps unsurprising that they contained highly emotive language. Few of the topics resulted in a statistically significant and negative relationship with fear and anger. While perhaps surprising that not one topic resulted in this it does largely conform with other literature that states that news headlines are overwhelmingly negative and/or sensational (Geer & Kahn 1993, Gabielkov, Ramachandran, Chaintreau & Legout 2016, Hern 2020).

Table 3.6: News Headlines Regression Results

	Dependent variable:	
	(*Fear*)	(*Anger*)
Conspiratorial Sites	0.623	0.641
	(0.000)	(0.000)
Ideological Bias	−0.203	−0.290
	(0.254)	(0.020)
Standard of Reporting	0.171	0.192
	(0.350)	(0.044)

Note: p-values in parentheses

Figure 3.13: News Headlines Coefficient Plots



3.3.4 Robustness and Limitations

Since the data from MBFC was automatically downloaded through a process known as web scraping via Python's Scrapy tool the data needed to be validated and quality checked (Kouzis-Loukas 2016). First, MBFC combines conspiratorial news outlets and those who engage in pseudoscience into a single score. These two areas are highly related. Common conspiracies such as childhood vaccines and flat earth are coded as pseudoscience. Thus, many 'pseudoscience' sites are in fact conspiracy sites. However, not all are. On each conspiracy/pseudoscience page on MBFC, there is a graphic that gives the site's position on both a conspiracy science and a pseudoscience scale. The scale for conspiracy level ranged from mild to moderate to strong to 'tin foil hat'. As the graphic is stored on the webpage as a .png attachment is was not scraped as text. Therefore, for all the sites initially identified in this category, the MBFC page was checked. A small number of sites were recoded as they engaged in pseudoscience but not conspiracy theories. Sites that promoted areas such as spiritual/faith healing and other alternative medical treatments were common amongst those reclassified. Further to the reclassification of the pseudoscience outlets, a random sample of ten per cent of all sites downloaded from MBFC were checked. This was to ensure that the data harvested via Python matched that on the website. No issues were noted.

The dataset for this analysis identifies outlets that regularly promote conspiracy theories but does not identify individual posts that are discussing specific conspiracy theories. There are two reasons for this. First, conspiracy theories are clandestine, dynamic and diverse in nature. Therefore, confidently identifying all posts relating to even one conspiracy theory, let alone all conspiracy theories, would be very difficult if not impossible. Second, Facebook moderators regularly delete posts that contain blatant misinformation, disinformation, and conspiracy theories. Thus, any effort to identify all conspiracy posts on a large dataset such as those used here would suffer from bias of omission and therefore any resulting analysis would be misleading. Faced with this challenge, this chapter focused on the stylistic tendencies of the identified conspirational news outlets. This offers valuable insights into the style of communication these actors employ. Future research may be able to address the issue of specific conspiracy posts.

3.4 Conclusion

This chapter utilises a newly created dataset of all the publicly available Facebook posts of the US news media for the period 01 January 2020 to 31 January 2021 to investigate whether conspiratorial outlets use heightened levels of fear and anger in their posts vis-a-vis their non-conspirational peers in the American news media. The dataset of 7,221,509 Facebook posts is, to this author's knowledge, the largest content analysis of conspiratorial messaging in the news media to date. This dataset is then supplemented through 180,076 articles from nine right-wing news sources across the 01 January 2020 to 30 June 2020 and 01 September to 31 December 2020 time periods. This is done to give a more fine-grained, in-depth analysis of the language used within messaging from news outlets. Taking into account the novelty of the size of the dataset used as well as the relative dearth of investigations into the stylistic choices made by those who propagate conspiracy theories in their communication strategies this is a fresh approach towards understanding one of the factors that may increase conspiracy belief in a population.

The chapter demonstrated that conspiratorial outlets use heightened levels of fear and anger in their Facebook posts and news headlines but not in their news articles. This finding is interesting. The short, snappy version of a story (the headline or the Facebook post) published by a news outlet that engaged in conspiracy theories was more likely to have higher levels of fear and anger whereas there was no relationship for the news articles. Scholars have long understood the power of headlines for priming individuals (Geer & Kahn 1993). Studies have found that for the majority of news consumers, especially on the internet, the content of an article does not matter. Headlines and social media posts are what triggers our attention. These in effect summarise the articles, and impact how we process the facts of a news article or opinion piece. Indeed, studies have demonstrated that the majority of individuals who share articles online only read the linked headline or the text of the post linking the article (Dewey 2016). Indeed, one study found that 59 per cent of links shared on Twitter have never actually been clicked (Gabielkov et al. 2016). Further, the average person only spends fifteen seconds reading any given article (Haile 2014). This means that the figure of 59 per cent probably understates the number of shares from people who have truly read the article. The same study also found that the blind sharing of these articles had a large impact on what appeared in other users newsfeeds. This trend is so stark that even Twitter, a site oft-maligned for its slow pace in tackling misinformation, disinformation, and conspiracy theories, introduced measures that encouraged people to read an article before retweeting or sending the article to other users (Hern 2020). Thus, the content of news articles and Facebook posts matter more than the content of actual articles as that is what the consumer engages with more, and what drives the spread of information on social media platforms.

The findings of this chapter suggests that in the most important avenues of written communication (social media posts and news headlines) those who spread conspiracy theories use heightened levels of fear and anger. These findings have important implications for the study and understanding of belief in conspiracy theories. How one is exposed to information makes a material difference to their understanding of that information. Conspiracy messaging is no different with exposure being an important component of belief (Uscinski & Parent 2014).

However, the nature of this exposure has, as of yet, been understudied. We know a lot about the characteristics of those who subscribe to both specific conspiracy theories and conspiracy theories in general. We also know of the motivations of those spreading both specific conspiracy theories and conspiracy theories in general. We know where these conspiracies spread (Douglas et al. 2019). However, our knowledge of the communicative styles of those who engage in the conspiracy is still limited. This chapter provides a high-level analysis of the stylistic nature of the communication of those who engage in conspiracy theories. This contributes towards closing our gap in knowledge in this domain.

Extending from these findings future research should have three focuses. First, due to data collection limitations, this research is at a high level, looking at the use of fear and anger by conspiratorial news outlets rather than at the language in social media posts and articles that reference specific conspiracy theories. While this gives a good indication into the nature of how conspiracy theorists communicated it does not isolate conspiratorial messaging specifically. It of the utmost importance that this limitation is addressed in future research.

Thus, the development of an exhaustive dictionary that identifies such posts would move research in this arena forward. Further, the constant scraping of posts from conspiratorial sources would allow for the capture of posts before they are removed by social media moderators. Secondly, in the modern world, much communication comes in the form of audio and audiovisual mediums. A similar analysis of the use of fear and anger in such mediums would also contribute to closing the gap in the literature. Finally, and importantly, whether or not the use of such language influences the dissemination of posts on social media platforms should be investigated. This is of great importance as such an investigation would be able to see if the use of fear and anger a) drives social media engagement and by extension b) increases the number of individuals who are exposed to the message.

Chapter 4

The Effect of Fear and Anger on Conspiracy Theorists' Facebook Post Performance

Abstract

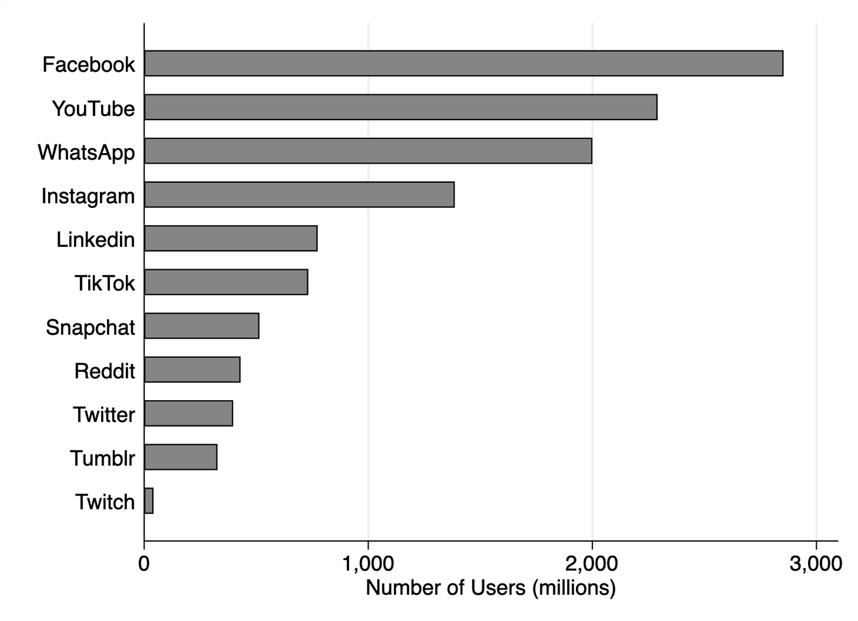
An important factor influencing individuals' perception of conspiracy theories is their exposure to these theories. Understanding where and how this exposure occurs is important in understanding conspiracy theories. One of the main avenues that people are exposed to new information, political or otherwise, is through social media platforms such as Facebook. As demonstrated in Chapter 3, on social media platforms like Facebook, conspiratorial news outlets utilise heightened levels of fear and anger. The political communication and political psychology literatures hold that the presence of such emotion ought to encourage individuals to pass along this newfound information. Using Facebook's Crowdtangle platform and the National Research Council Canada Emotion Lexicon this paper demonstrates that increased levels of fear and anger within conspiratorial news outlets' Facebook posts significantly increases the relative number of interactions these posts receive. This demonstrates that fear and anger both encourages engagement with conspiratorial news outlets' social media content and increases the number of people exposed to this content.

4.1 Introduction and Motivation

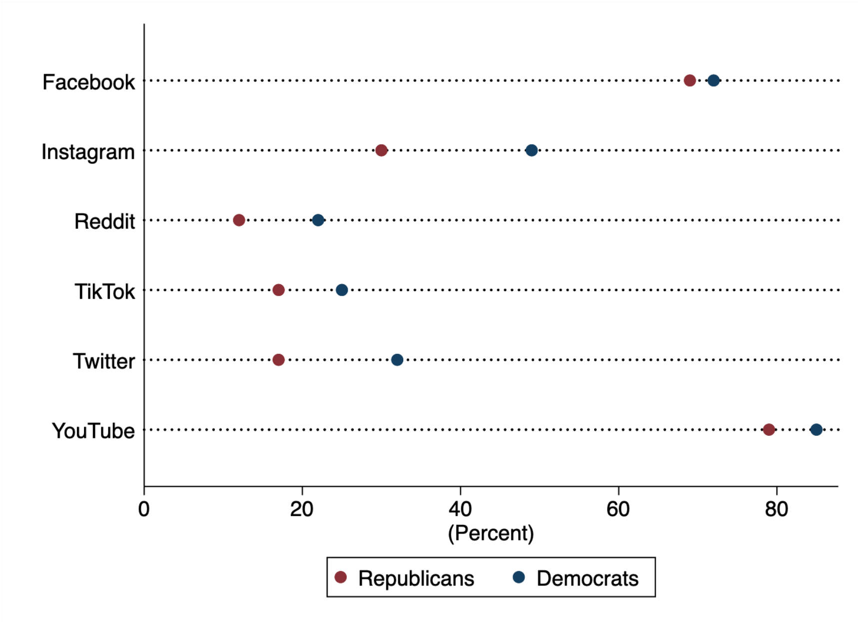
Since the advent of the internet and especially the advent of social media, how individuals come into contact with new information has changed greatly (Neuman, Bimber, Hindman et al. 2011). Over fifty per cent of Americans get their news at least some of the time through social media accounts (see Figure 4.1(d)). While this figure still lags behind news websites, apps, and search engines the fact remains that a majority of Americans are getting their news through social media at least some of the time. Further, these figures possibly understate the real figure through social desirability bias as well as people clicking links on social media sites that lead to news websites and apps or people using search engines to search for the context viewed in a social media post (Grimm 2010, Pentina & Tarafdar 2014). Therefore, the true figure is possibly even higher than that captured in surveys.

As Figures 4.1(a), 4.1(b), and 4.1(c) outlines, Facebook is by far the most social media platform in this context. Facebook has the most active users globally and is the social media platform through which the most people acquire their news. Further, it is the social media platform with the least divergence in favourability ratings across partisan lines. Therefore, Facebook is one of the most important sources of news in the United States.

Figure 4.1: Social Media Usage

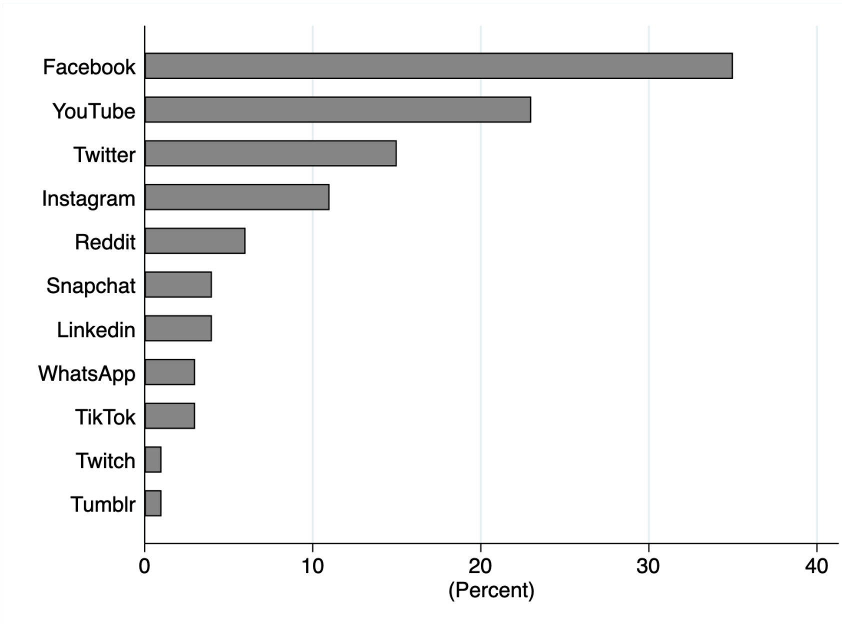


(a) Active Users - Worldwide

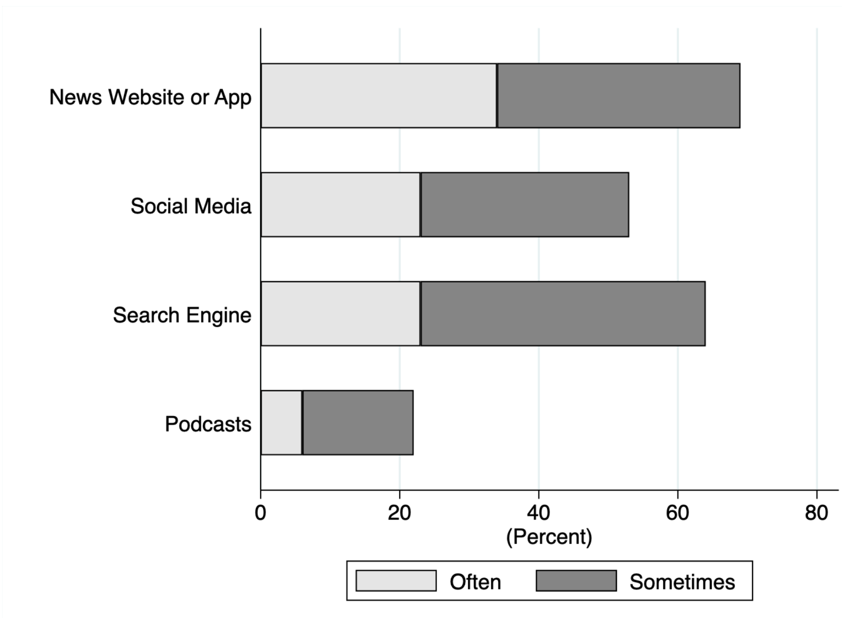


(b) Partisan Favorability

Figure 4.1: Social Media Usage (continued)



(c) Social Media News Sources



(d) Overall News Sources

Source: Pew Research Center

https://www.pewresearch.org/journalism/2021/01/12/news-use-across-social-media-platforms-in-2020/ & https://www.pewresearch.org/fact-tank/2021/04/07/partisan-differences-in-social-media-use-show-up-for-some-platforms-but-not-facebook/

In the first quarter of 2021, the most-viewed link on Facebook was a news article with a headline suggesting that a doctor had died due to side effects from a Covid-19 vaccine (Callery & Goddard 2021). Of the top ten news outlets with the most interactions on Facebook, five are known to spread conspiracy theories. While one, Fox News, which has stronger editorial standards in its written journalism vis-a-vis its tv opinion shows, toes the line between ideological bias and propagating conspiracy theories (Smith & Searles 2013). As per the Crowdtangle dataset discussed in Chapter 3, of the top ten news outlets on Facebook with at least 1,000 Page Likes ranked by interaction rate, six were sites known to spread conspiracy theories.[1] There is ample evidence that demonstrates that misinformation, disinformation, and conspiracy theories prosper on social media platforms like Facebook (Del Vicario, Bessi, Zollo, Petroni, Scala, Caldarelli, Stanley & Quattrociocchi 2016). Indeed, the prevalence of misinformation online, of which conspiracy theories are a subset, has been identified as such a cause of concern that Twitter introduced checks to lower the incidence of shares and retweets of unread articles, Twitter and Facebook have to label topics susceptible to conspiracy theories such as election fraud and Covid-19 vaccines with a warning label, and the World Economic Forum has listed digital misinformation as one of the main threats to society (Fowler 2020, Franco et al. 2020).

What influences this trend? Why are conspiratorial news outlets so popular online? This Chapter contends that, in line with the findings in Chapters 2 and 3, the presence of fear and anger in conspiratorial news outlets social media posts influences the relative number of interaction they receive. Fear and anger are both emotions that cause one to feel uncomfortable, threatened, and not in control (Brader & Marcus 2013). One reason why people subscribe to conspiracy theories is to compensate for feeling unsafe or lacking in control. This is known as the existential motive behind conspiracy belief (Douglas, Sutton &

[1] $\frac{\sum Interactions}{\sum Page\ Likes}$

Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). Triggering these emotions can influence individuals to engage with the theories online. Further, there is recent evidence that politically salient topics like this garner higher levels of toxicity (Kim, Guess, Nyhan & Reifler 2020). Thus, based on our knowledge of these emotions, the existential motives behind conspiracy belief, the fact that the presence of fear and anger in conspirational articles increases individuals' likelihood to believe in said conspiracy theory (results from Chapter 2) and the heightened presence of fear and anger in the Facebook posts created by conspiratorial news outlets (results from Chapter 3) it seems natural that fear and anger may indeed an important role in the dissemination of the information online. Using a dataset consisting of all Facebook posts from the US news media from 01 January 2020 to 31 January 2021 (n = 7,221,509) this chapter demonstrates that the presence of fear and anger in Facebook posts created by conspiratorial news outlets significantly increases the interactions these posts garner.

4.1.1 The Spread Conspiracy Theories on Social Media

Political and social information has always been vulnerable to phenomena such as misinformation, disinformation, and conspiracy theories. For example, a study of the New York Times Letters to the Editor found that conspiracy theories were ubiquitous across time with no discernable pattern or increase to be observed. There is evidence that conspiracy beliefs peak during or after times of crisis. For example, terrorist attacks, plane crashes, natural disasters, or war but there is little evidence that conspiratorial beliefs have been increasing over time (Uscinski & Parent 2014, Van Prooijen & Douglas 2017). However, there is widespread concern that we have entered a new era of conspiracy theories with the widespread use of relatively unregulated social media platforms allowing for the proliferation of both conspiracy theories themselves and the belief in these theories. Those who say that social media has led to more people believing in conspiracy theories state that it has become easier than ever to propagate and consume conspiracy theories. Before the age of social media if you wanted to spread a conspiracy theory it was difficult for your message to reach enough people to gain popular support. This dynamic has completely changed in the age of social media where expensive infrastructure is no longer needed to transmit information. Social media echo chambers, social motives, and motivated reasoning all reinforce this. (Stecula & Pickup 2021)

Despite the assertion that social media has increased the prevalence of conspiratorial belief there is, as yet, no empirical evidence to substantiation the claim. Indeed, at almost all moments in time journalists have claimed that conspiracy theories are becoming more widespread. In the American context, we do know that: the numbers of Americans who get their news from social media has doubled since 2013; social media is ripe for misinformation; and getting your news from social media is associated with an increase in the likelihood of being misinformed (Stecula, Kuru & Jamieson 2020, Swire-Thompson & Lazer 2019, Vosoughi, Roy & Aral 2018, Wang, McKee, Torbica & Stuckler 2019). Further, social media users are more likely to be exposed to conspiracy theories (Mitchell, Jurkowitz, Oliphant & Shearer 2020) While empirical evidence proving conspiracies are widespread does not currently exist there is certainly theoretical reasons to believe that social media is fueling an increase in these beliefs. Indeed, even if the overall belief in conspiracies in society has not increased, there is little doubt that social media is one of the main vectors through which modern-day individuals are exposed to conspiracy theories.

Ultimately, the real issue here is the lack of consistent polling on conspiratorial beliefs over time. However, whether or not conspiracy beliefs are on the rise, there is little doubt that social media plays a prominent role in how they spread in modern society. Social media plays an important role in the spread of all information in modern society and conspiracy theories are no different. Further, the usual (but not always) reluctance of mainstream media outlets to engage in conspiracy theories means low-cost platforms where fringe sites can post information and articles will play an important role. Here, social media platforms such as Facebook and YouTube play an important role.

4.1.2 The Role of Emotion in the Dissemination of Information

An important goal of conspiracy theorists is the dissemination of their conspiracy theories (Starbird 2017). To this end, there is ample evidence that communication strategies that evoke emotion influence individuals to pass on information with research suggesting that emotion encourages the diffusion of information (Sunstein & Vermeule 2009, Vosoughi, Roy & Aral 2018). Several studies have shown that individuals are emotionally triggered by a story they are more likely to pass on the information to other people (Fan, Zhao, Chen & Xu 2014, Oliver & Wood 2014). Indeed, the presence of emotional language within political messages substantially increases their diffusion (Brady, Wills, Jost, Tucker & Van Bavel 2017). Furthermore, emotional content is more likely to go viral (Pfitzner, Garas & Schweitzer 2012, Brady et al. 2017). Importantly, these trends are more pronounced in the presence of negative emotions.

4.2 Fear, Anger, and the Spread of Conspiracy Theories on Facebook

The exact role that emotion plays in the popularity of Facebook posts is not fully understood. There is evidence that toxicity fuels partisan engagement (see, Kim et al., 2021) and negativity within a post is associated with increased engagement for political candidates (see Heiss, Schmuck, and Metthes), and political ads with increased inflammatory language led to higher levels of engagement (see Vargo and Hopp, 2020). Combine these findings with what we know about the news media in general - cynical and negative news is more popular - and a clear picture of the popularity of negative news on social media becomes apparent (Trussler & Soroka 2014).

There is ample evidence that points to the popularity of negativity in both the news in general as well as on social media sites like Facebook specifically. When this is combined with the relationship between fear and anger outlined in Chapters 2 and 3 as well as the previously identified proximity between fear and anger and the social-psychological motives of conspiracy theories the expectation that increased fear and and anger in conspiratorial news outlets' Facebook posts will increase Facebook post engagement. Therefore, this chapter proposes the following hypothesis:

Hypothesis 4.1 *As the level of fear and anger in conspiratorial news outlets' Facebook posts increases so too does the engagement in these posts.*

4.3 Data and Methodology

This section will outline the data used to investigate the hypotheses presented above. Subsequently, the methodology employed will also be outlined.

4.3.1 Data Source

To investigate this chapter's hypothesis - to what extent does fear and anger in conspiratorial news outlets' Facebook posts influence their engagement - the dataset of Facebook posts from US-based news outlets outlined in Chapter 3 is built upon.[2] As set out in Chapter 3, the dataset contains 7,221,509 posts from 1,608 unique Facebook pages. Each row in the dataset contains information on the specific post. For instance, the text of the post, the type of post, the date and time of the post, and the text of any links contained in the post. Further, each row contains fixed information on the page that created the post. Such as the ideological bias of the site, the quality/standard of the site's reporting, and whether the site disseminates conspiracy theories.

4.3.2 Dependent Variable - Facebook Post Performance

Facebook's Crowdtangle platform (Crowdtangle) provides data on the interactions that every public post on Facebook receives. These interactions are "likes", "love", "care", "haha", "wow", "sad", "angry", "share", and "comment". Using these interactions Crowdtangle creates a performance score for every post. This score is known as the 'overperform' score on the platform. It will be referred to as the post-performance score for this chapter. This score compares the actual number of interactions a post generates compared to an expected value known as a benchmark. The benchmark is calculated by taking the last 100 posts from a given account and a given post type (link, image, video etc.). The top 25 per cent and bottom 25 per cent posts in terms of interactions are dropped. The mean value of interactions for the middle 50 per cent relative to the age of the post (15 minutes old, 60 minutes old, 5 hours old, 2 weeks old, etc.) is used as the benchmark. For example, a video posted by an account fifteen minutes ago is compared to the mean interaction rate of the middle fifty per cent of the last 100 videos posted by the account after fifteen minutes. Similarly, a link posted a week ago is compared to the mean interaction rate of the middle fifty per cent of the last 100 links posted by the same account after one week (CrowdTangle Team 2021).

[2] The construction of this dataset is outlined in detail in Chapter 3.

The post-performance score is calculated using slightly different equations in different contexts for data normalisation purposes. There are five equations used to calculate the overperform score based on the following five situations:

1. *Post Performance Score ¿= 1.0*

   This is the standard equation used. The number of interactions is divided by the benchmark. So, if a post had 100 interaction and the expected benchmark value was 50 the post would have an post performance score of 2.0. In this situation the equation is as follows:

   $$1.1 \;\; Post\ Performance\ Score = \frac{\sum Interactions}{Benchmark}$$

2. *Post Performance ¡= - 1.0:*

Crowdtangle reports underperforming posts as negative. Using Equation 1.1 an underperforming post would return a score between zero and one. Say the actual number of interactions on a post was 50 and the benchmark was 200. The post-performance would be 0.25. In order to ensure a negative score Equation 1.1 is flipped. Therefore, using the example of a post with 50 interactions and a benchmark of 200 a post-performance score of -4 is returned. In this situation, the equation is as follows:

$$2.1 \;\; Post\ Performance\ Score = \frac{Benchmark}{\sum Interactions}$$

3. *Post Performance Score = 0:*

Equations 2.1 and 2.2 run into problems when a post has zero interactions. In such a situation, Equation 2.1 will always return a value of zero no matter the value of the benchmark. Further, if the benchmark is zero the equation cannot be computed. Similarly, Equation 2.1 cannot be used in its stead as a zero here also cannot be computed. Crowdtangle therefore multiples the benchmark by negative two in order to get a more representative score. For example, a post with one interaction and a benchmark of 200 would have a performance score of -200. Using Equation 3.1 a post with zero interactions and a benchmark of 200 would have a score of -400. In this situation, the equation is as follows:

$$3.1 \;\; Post\ Performance\ Score = -2(Benchmark)$$

4. *0 ¡ Post Performance Score ¡ 1.0:*

Crowdtangle also introduces a minimum value. If a post had an expected value of one and an actual value of five, under Equation 1.1 the post-performance score would be 500. Similarly, a post with 500,000 interactions and an expected value of 1,000 would have a performance score of 500. It seems like the former is overvalued relative to the latter. Therefore, Crowdtangle uses a minimum value set at the same value for all Facebook posts to compensate for this discrepancy. If a post has nine interactions, a benchmark of two and a minimum of ten under Equation 1.1 it would have a post-performance score of 4.5. Under Equation 4.1 it would have a post-performance score of 0.9. Thus, the post is still over-performing it just sorts the value below posts that have more interactions than the minimum. In this situation, the equation is as follows:

$$4.1\ \textit{Post Performance Score} = \frac{\sum Interactions}{Minimum}$$

5. *-1 ¿ Post Performance Score ¡ 0:*

Equation 4.1 does not work well when the number of interactions is lower than the benchmark. Equation 5.1 is used in this case. If a post received two interactions and has a benchmark of five then the post's performance score is -0.6. If the number of interactions increased to three then the post's performance score is 0.4. This avoids wild fluctuations in performance scores and regularises the data. In this situation, the equation is as follows:

$$5.1\ \textit{Post Performance Score} = \frac{Benchmark - \sum Interactions}{Benchmark}$$

Table 4.1 and Figure 4.2 outline the distribution of the post-performance score. While not normally distributed the data is centred around the mean (-6.15). There are extreme minimums and maximums but only account for a small number of outliers. Further, Figure 4.3 shows the post-performance score is evenly distributed over time with peaks and troughs relative random.

Table 4.1: Post Performance Summary Statistics

N	Mean	St.Dev	Minimum	Maximum
6,862,541	-6.15	24.98	-978.61	997.2

Figure 4.2: Post Performance Scores Over Time

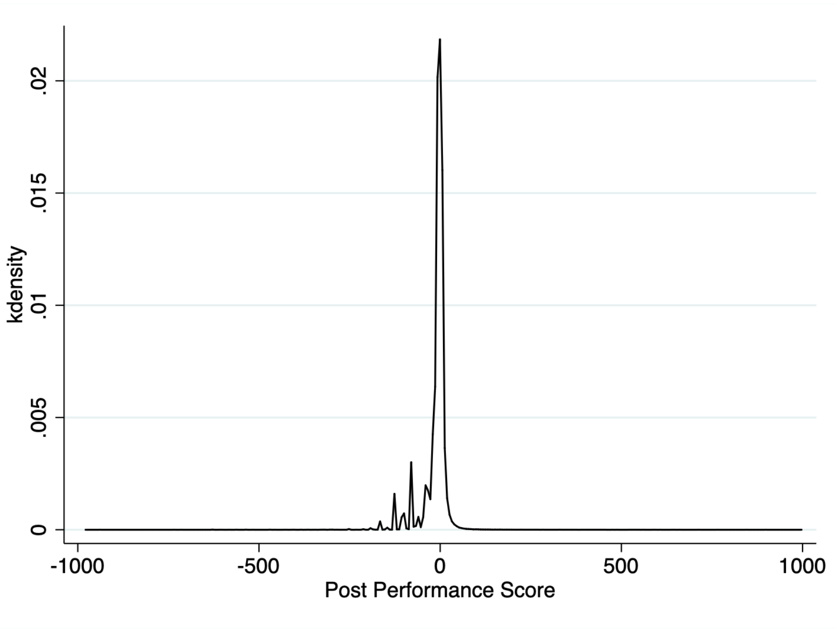
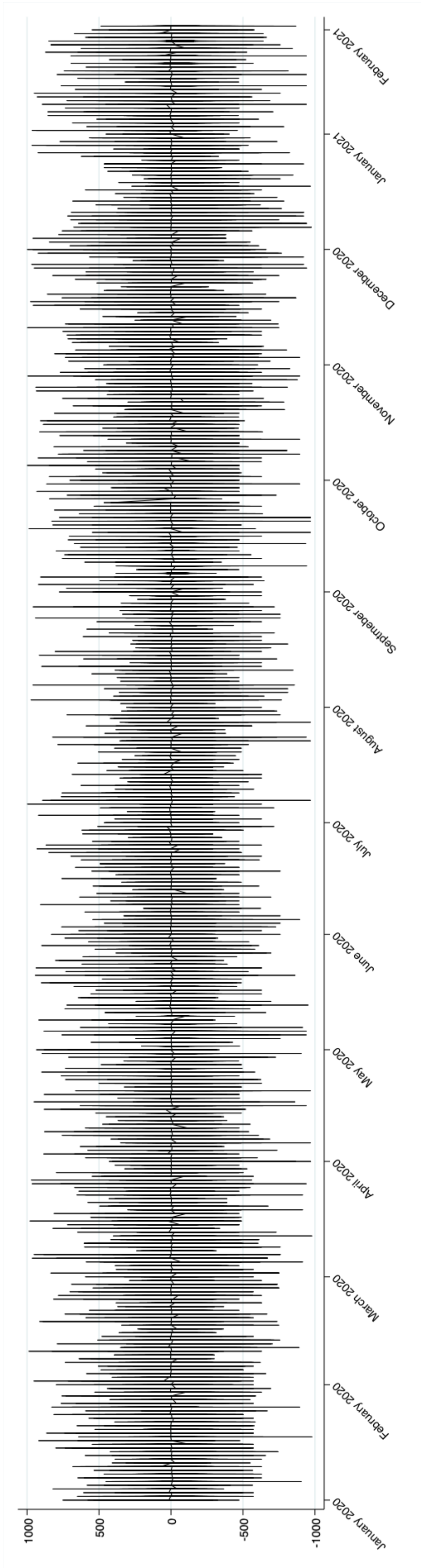


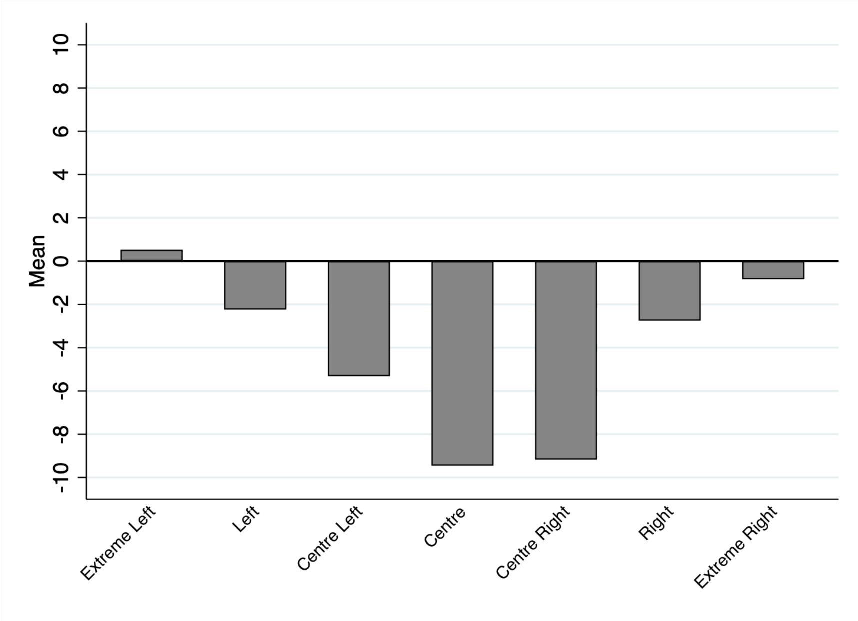
Figure 4.3: Post Performance Scores Over Time



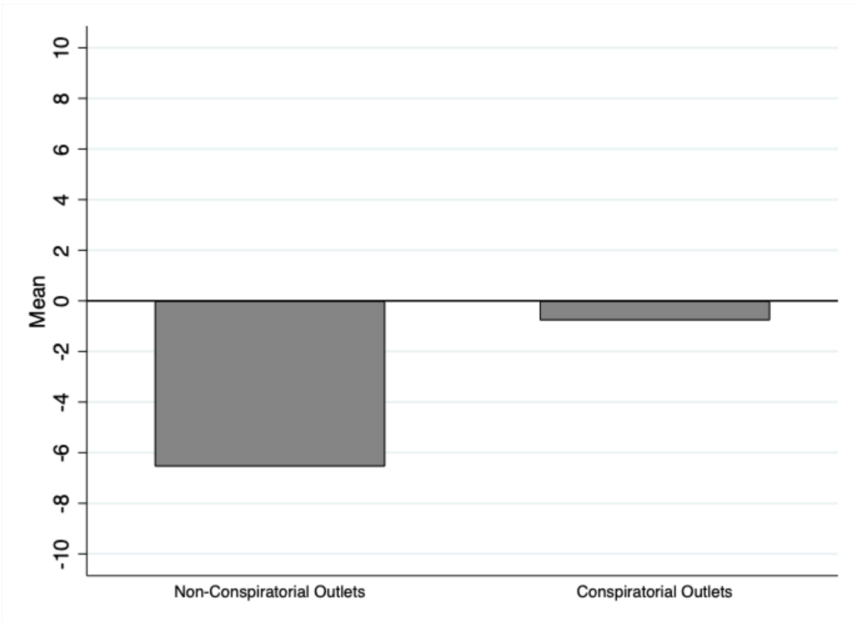
Interestingly, as Figure 4.4(a) demonstrates, the further from the ideological centre an outlet is, the better an outlet's post performs. Indeed, there are rather large discrepancies between centrist outlets and the extreme right and extreme left.

On average, conspiratorial news outlets' posts perform better than their non-conspiratorial counterparts. Indeed, as Figure 4.4(b) demonstrates there is a rather large discrepancy between conspiratorial (mean =.78) and non-conspiratorial (mean = -6.55) outlets. The tendency for conspiratorial and ideological extreme sites to perform better is interesting. Especially as post-performance is rated against the posts of the outlet themselves. This is certainly suggestive of extreme topics gaining more traction on social media outlets.

Figure 4.4: Mean Post Performance Scores



(a) Ideology



(b) Conspiratorial/Non-Conspiratorial News Outlets

4.3.3 Independent Variables

As in Chapter 3, the dataset used in this chapter contains fixed information on the page that created each Facebook post. Intuitively, since the dependent variable is calculated based on how each post performs relative to the performance of other posts from the same account this information there should be no need to control for such variables. However, as Figure 4.4 demonstrates there certainly seems to be an influence of factors such as ideology and conspiracy. Therefore, the ideological bias and standard of reporting are controlled for.

The number of likes the page that created the post is also controlled for. This figure is dynamic and can change from post to post. There is reason to believe that an increase in the number of likes a page has will increase its exposure on the Facebook platform and therefore increase the number of interactions that the post receives. Therefore, the number of likes that a page has at the time of the post's creation is included as a control variable.

The type of post created is also controlled for. There are eight types of posts identified by Crowdtangle. They are: Status; Native Video; Video; Photo; Link; YouTube Video; Live Video; Live Video (Completed); and Live Video (Scheduled). As can be seen in Figure 4.5 links are by far the most popular form of post in the dataset with 88.36 per cent of all posts being links. This is perhaps unsurprising. The dataset is comprised exclusively of news outlets with many of the posts linking to news articles on the poster's website. The varying types of posts have different requirements from end-users and therefore, the post type may well influence how people interact with a post. While the post-performance score is calculated against the performance of the same type of posts, Figure 4.5 demonstrates a large variation in the post-performance score across the eight types of posts. Thus, the post type is controlled for in the analysis using dummy variables. Figure 4.6 demonstrates the proportion of each type of post across the sample.

Figure 4.5: Post Types

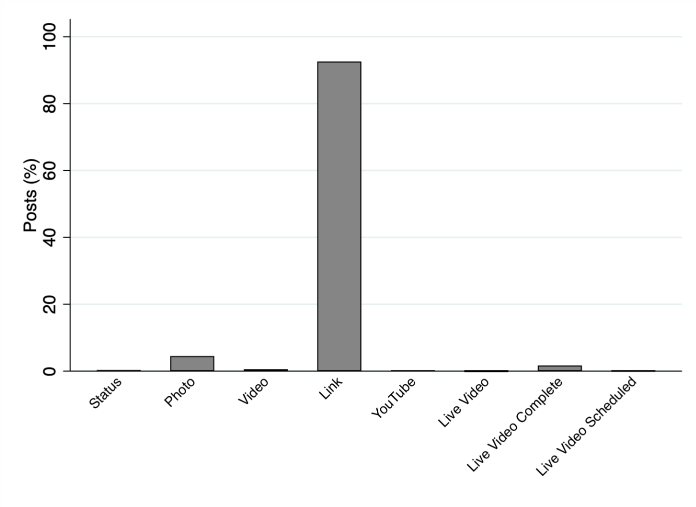
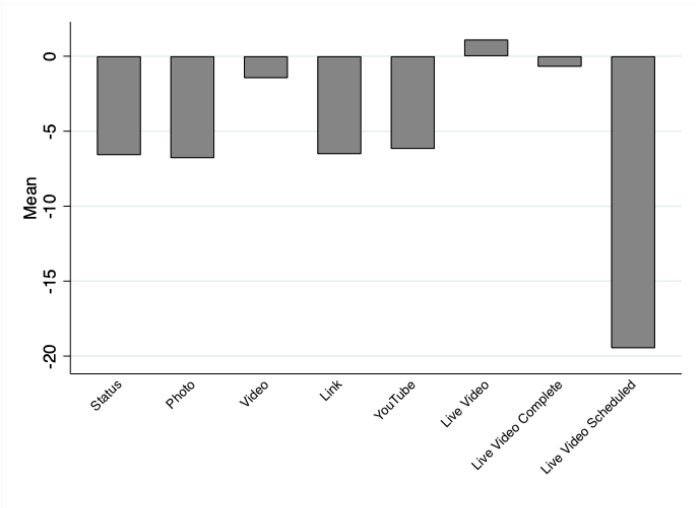


Figure 4.6: Facebook Post Performance by Type Types



4.3.4 Empirical Strategy

This chapter investigates whether the presence of fear and anger in Facebook posts from conspiratorial news outlets influences post-performance. The chapter employs an ordinary least squares (OLS) model with standard errors clustered as the level of the news outlet and controls for the ideological bias of the outlet, the outlet's standard of reporting, the number of page likes at the time the post was created, the type of post, and the topics being discussed in the particular post or news article. This is done across three models. The first model looks at all posts in the dataset and endeavours to provide an answer to Hypothesis 1. This is done to establish whether the presence of fear and anger in a post affects the post-performance regardless of the conspiratorial nature of the post creator. Further, the results of Hypothesis 1 provide a baseline from which comparisons can be made. The second model utilises an interaction effect between conspiracy sites and language to determine if there is a bigger effect when conspiratorial sites utilise negative emotive language compared to non-conspiratorial sites. The final model subsets the dataset to look exclusively at conspiratorial news outlets. This isolates the effect that negative emotive language has specifically on the posts of conspiratorial sites. The regression equations are as follows:

$$(1)\ Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + \beta_3 Conspiratorial\ Outlets + \beta_4 Ideological\ Bias + \beta_5 Standard\ of\ Reporting + \beta_6 Page\ Likes + \beta_{7-14} Post\ Type + \beta_{15-37} LDA\ \ Topics + \epsilon$$

$$(2)\ Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + \beta_3 Conspiratorial\ Outlets + \beta_4 Conspiratorial\ Outlets\ x\ Fear + \beta_5 Conspiratorial\ Outlets\ x\ Anger \beta_6 Ideological\ Bias + \beta_7 Standard\ of\ Reporting + \beta_8 Page\ Likes + \beta_{9-16} Post\ Type + \beta_{17-39} LDA\ \ Topics + \epsilon$$

$$(3)\ Y_i = \beta_0 + \beta_1 Fear + \beta_2 Anger + + \beta_3 Ideological\ Bias + \beta_4 Standard\ of\ Reporting + \beta_5 Page\ Likes + \beta_{6-13} Post\ Type + \beta_{14-36} LDA\ \ Topics + \epsilon$$

4.4 Results

Table 4.2 reports the results from the three different OLS models outlined in Section 4.3.4. The first model demonstrates that heightened levels of fear and anger language in Facebook posts positively influences the post-performance relative to other posts from the same account with both fear and anger are statistically significant and positive. As the second model demonstrates, this relationship holds when interacting fear or anger with conspiratorial outlets. As the third model presented in Table 4.2 demonstrates, this relationship holds when looking solely at conspiratorial sites. Therefore, when holding for confounding variables, the presence of fear and anger have a statistically positive impact on conspiratorial outlets Facebook post performance.

Table 4.2: Facebook Post Performance Regression Results

	Post Performance Score:		
	(1)	(2)	(3)
Fear	0.037	0.042	0.063
	(0.000)	(0.000)	(0.000)
Anger	0.018	0.017	0.022
	(0.000)	(0.000)	(0.000)
Fear/Conspiracy Interaction		0.055	
		(0.000)	
Anger/Conspiracy Interaction		0.020	
		(0.000)	
Conspiratorial Outlets	1.476	1.906	
	(0.272)	(0.172)	
Ideological Bias	−0.724	−0.720	−0.203
	(0.000)	(0.000)	(0.208)
Standard of Reporting	−0.971	−0.971	0.128
	(0.024)	(0.024)	(0.764)
Page Likes	0.000	0.000	−0.000
	(0.029)	(0.028)	(0.061)
Link	0.991	0.964	0.292
	(0.633)	(0.645)	(0.736)
Live Video (Complete)	8.213	8.171	0.985
	(0.000)	(0.000)	(0.434)
Live Video (Scheduled)	−10.106	−10.144	−5.718
	(0.010)	(0.010)	(0.118)
Native Video	6.819	6.796	0.913
	(0.001)	(0.001)	(0.537)
Photo	3.827	3.794	−1.272
	(0.069)	(0.073)	(0.319)
Status	1.972	1.936	−0.750
	(0.393)	(0.404)	(0.575)
Video	3.378	3.350	0.362
	(0.089)	(0.094)	(0.848)
YouTube	2.808	2.825	−1.327
	(0.269)	(0.265)	(0.390)

p-values in parentheses

Figure 4.7: Regression Coefficient Plots

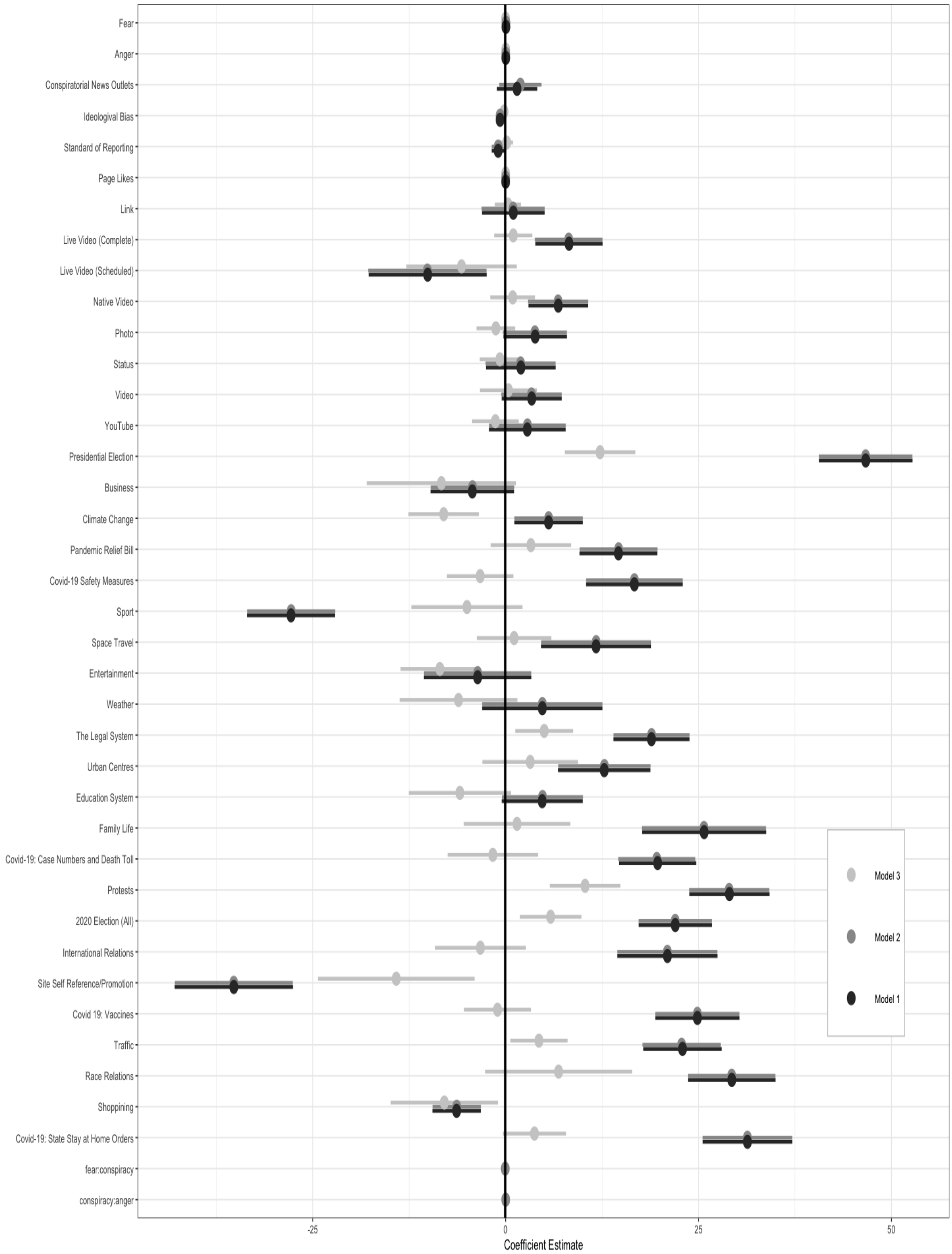
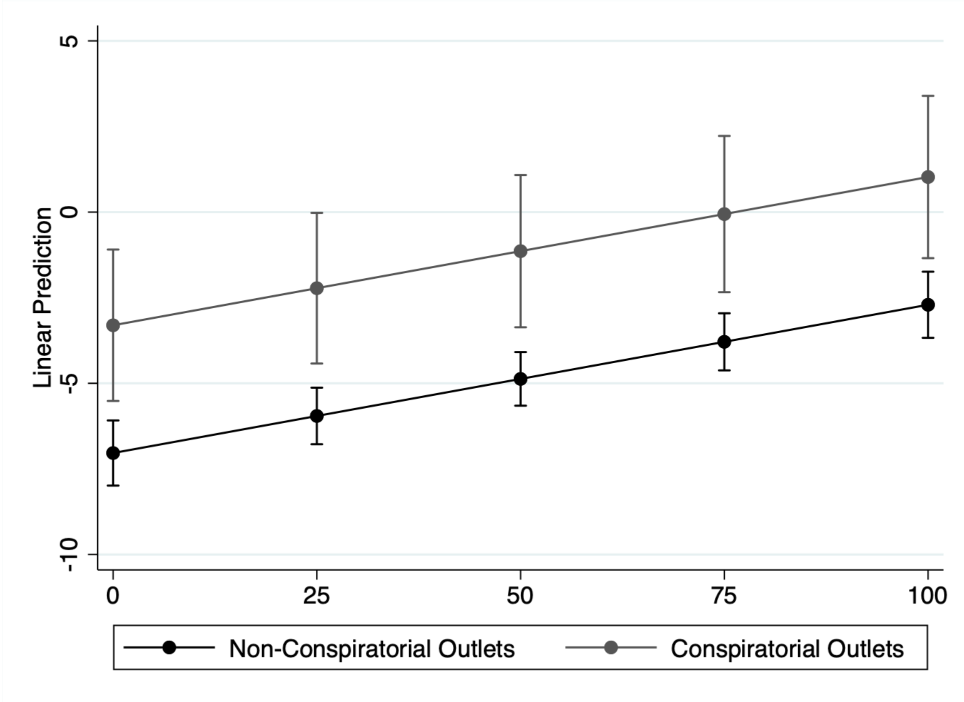
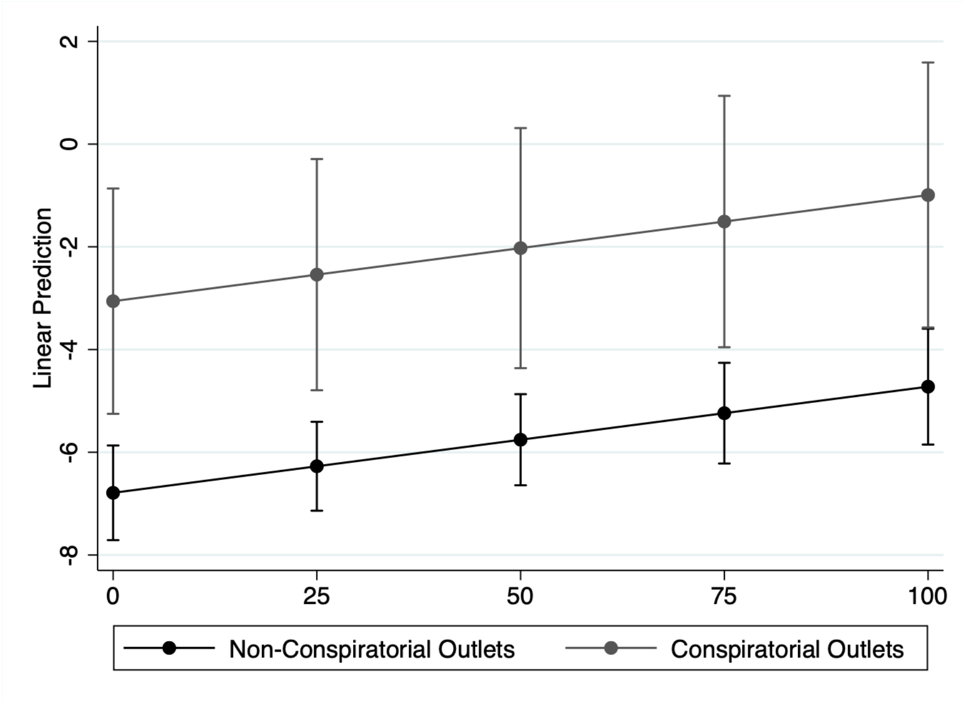


Figure 4.8: Model 2 Interactionism Effect Marginal Effects Plot



(a) Fear



(b) Anger

Further to anger and fear several covariates had a significant impact on the post-performance score. In Models 1 and 2 the ideological bias had a statistically significant negative relationship with the post-performance score. This meant that as an outlet became more right-wing the post-performance score decreased. This relationship was not statistically significant in Model 3. This is probably due to the preponderance of conspiratorial pages on the extreme right of the ideological spectrum. The standard of reporting has a statistically significant negative relationship with the post-performance score. This meant that as the quality/standard of the reporting of an outlet increased the post-performance score decreased. There was no relationship in Model 3. Again, this is likely due to the low quality of reporting across all conspiratorial outlets. This is certainly a worry for anyone concerned with misinformation, disinformation,m and low-quality journalism spreading on social media platforms. Across all models Page likes, Live Videos (Complete), Native Videos, Photos, and Videos all had statistically significant positive relationships with the post-performance score while Live Video (completed) had a negative relationship. The coefficient plots for the regression results are presented in Figure 4.7.

Certain topics such as the 2020 Presidential Election, climate change, court cases, and protest/civil unrest were statistically significant across all models. These are extremely important and topical news items. Therefore, it is unsurprising that topics such as these would garner higher levels of engagement. The full regression table including the coefficients of the Topics is included in Appendix C.1. It is important to note that some of the coefficients for the LDA Topic Models are quite large. However, across the board, the actual effect sizes are relatively small given the low values maximum values the topic models.

The results presented in this chapter demonstrate that as the presence of fear and anger within posts increases so too does the performance of these posts. This means that those posts are getting more interactions. This in turn means these posts reach a wider audience via individual users' timelines. Thus, the use of both fear and anger increases engagement with those who see the post but also bring the post to more people helping spread the message contained within the post. While this is the case across both conspiratorial and non-conspiratorial outlets it is important to note that the relationship is stronger in the case of conspiratorial outlets. Further, this relationship is stronger for fear than anger. As discussed in Chapter 2, fear is a surveillance behavioural system. It triggers a heightened response in individuals. It makes them more likely to engage in information and seek out other information. Thus, fear can be seen as an emotion that awakens the senses. Naturally, when we feel fear we are sensing danger or potential. This heightens our senses and makes us engage more with the world around us. Anger, on the other hand, is an emotion that dulls us somewhat. We tend to rely on previous beliefs and are unlikely to change our minds. Therefore, it is unsurprising that fear has a bigger impact than anger.

4.4.1 Robustness, Data Validity, and Limitations

The dataset for this analysis identifies outlets that regularly promote conspiracy theories. However, the individual Facebook posts that promote conspiracy theories have not been individually identified. There are two reasons for this. First, conspiracy theories are clandestine, dynamic, and diverse in nature. Thus, confidently identifying all the posts relating to a particular conspiracy theory, let alone all conspiracy theories within the dataset is highly difficult if not impossible. Therefore, any findings from a dataset that claims to contain all posts relating to a particular theory or all theories is likely suffering from omission bias. The second obstacle towards such a dataset is that many conspiracy theories violate Facebook's terms of service. Crowdtangle provides data on all publicly available Facebook posts at the date of download. Therefore, any effort to create a complete dataset of posts relating to one or more conspiracy theories will likely have omission bias as certain posts will have been removed by Facebook's moderators. Thus, this chapter demonstrates that when outlets are known for promoting conspiracy theories.[3]

4.5 Conclusion

This chapter utilises a newly created dataset of all publicly available Facebook posts created by the US news media for the period 01 January 2020 to 31 January 2021. Using this dataset, the chapter demonstrates that as the proportion of fear and anger in Facebook posts increased so too did the performance of the Facebook posts. Further, the chapter demonstrated that this relationship is stronger in the context of conspiratorial news outlets. Taking into account the novelty of the size of this dataset and the fact that it represents the entire population of publicly available Facebook posts from US news outlets for this time period. Therefore, this is, to the author's knowledge, the largest study of the influence of fear and anger on the popularity of conspiracy theorists' social media posts to date.

This chapter demonstrated that when outlets utilise heightened levels of fear and anger in their Facebook posts these posts perform better. This relationship is stronger in conspirational outlets than non-conspirational outlets. Therefore, the presence of fear and anger in conspiracy theorists Facebook posts increases the performance of these conspiracy theorists Facebook posts. Approximately xx per cent of Americans get their news on social media with Facebook by far the most popular social media platform. Therefore, it is reasonable to think that that for many, exposure to conspiracy theories comes through posts viewed on Facebook.

[3] This chapter largely utilises the same dataset as Chapter 3. For considerations taken to data validity and robustness please see section 3.3.4.

Both the conspiracy theory and political communication literature has demonstrated that exposure to political information plays a key role in people developing opinions on this information. While this is intuitive it is of great importance. Thus far, this dissertation has demonstrated that exposure to a conspiracy theory through a frame of either fear or anger increases one's susceptibility to that conspiracy theory. Subsequently, it was demonstrated that conspiracy theorists use higher levels of fear and anger in their social media posts than their non-conspiratorial counterparts in the news media. Finally, this chapter completes the circle by demonstrating that higher levels of fear and anger within conspiracy theorists Facebook posts increase the level of interactions these posts get. This finding implies that Facebook users are more engaged with these posts and also, and perhaps more importantly, are shown to larger audiences due to the higher interaction rates. Thus, the conspiracy theorists are utilising higher levels of fear and anger in their social media posts, this is driving engagement, which in turn exposes more people to messages that we know increase their likelihood to believe the conspiracy theory.

Extending from the findings of this chapter should take two distinct focuses. First, this dataset identifies news outlets that propagate conspiracy theories rather than individual posts relating to conspiracy theories. As discussed in Chapter 4, identifying individual conspiratorial posts is difficult due to the clandestine and dynamic nature of conspiracy theories. This is made more difficult by social media moderators removing posts that violate their terms of service. For example, a post referencing an explicitly anti-Semitic conspiracy theory may be removed by Facebook. Thus, identify all posts on the site that relate to conspiracy theories would be difficult if not impossible. And even if this was achieved there would be omission bias through the absence of deleted posts. Thus, this chapter identified the sites that engage in conspiracy theories and analysed all of their Facebook posts. The development of an exhaustive conspiracy dictionary and the automated downloading of Facebook posts as they are created would allow for a more in-depth analysis of conspiracy theories online. Secondly, the influence of fear and anger within visual and audiovisual mediums such as videos and podcasts should be investigated. As outlined earlier in this chapter, videos make up a small proportion of the posts in this dataset. therefore, an investigation into other mediums such as YouTube and Podcast platforms would be a suitable avenue to peruse.

Chapter 5

Discussion and Conclusion

This dissertation sought to theorise and test the influence that fear and anger have on the formation and dissemination of conspiratorial beliefs. Focusing on the United States of America in 2020, the causal mechanism was tested across three research questions in turn:

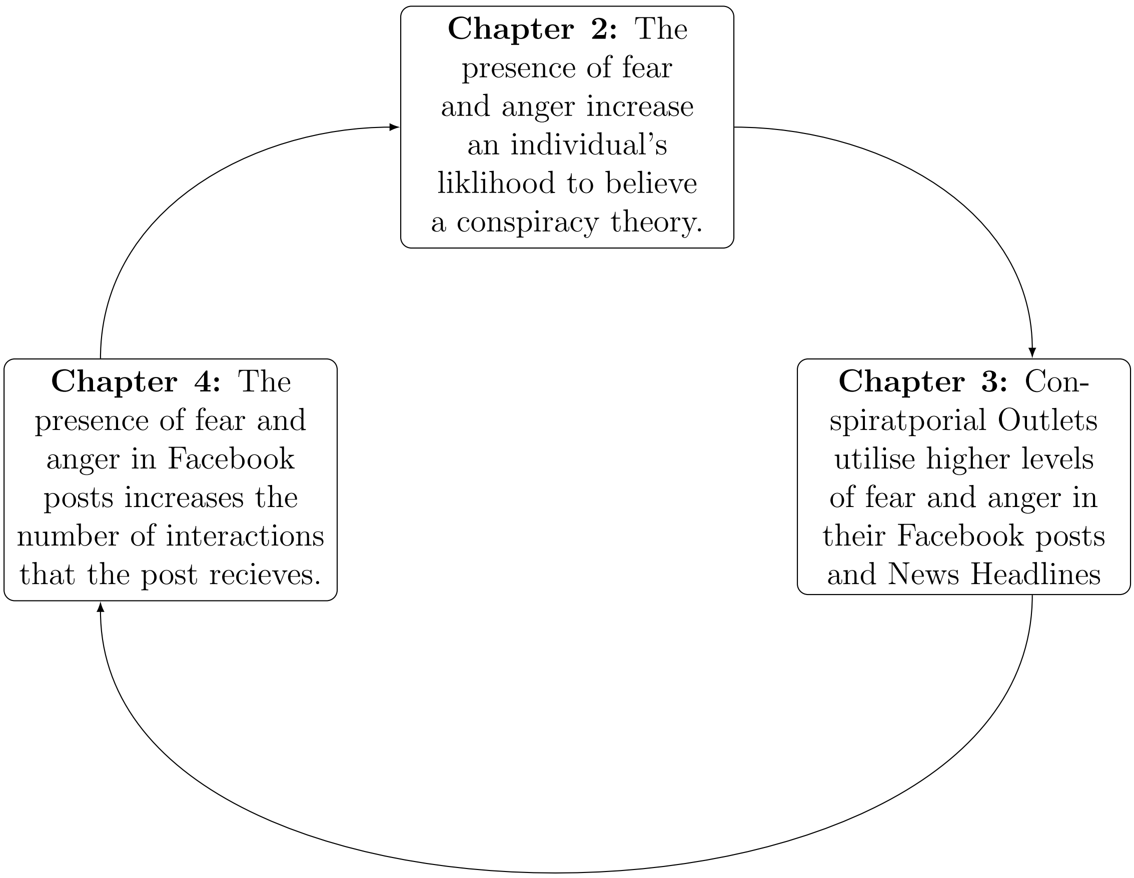
1. Does the presence of fear and anger in a conspiratorial news article increase the probability of an individual believing in that conspiracy theory?

2. Compared to non-conspiratorial news outlets, do conspiratorial news outlets utilise heightened levels of fear and anger in their Facebook posts, news articles, and news headlines?

3. Does heightened levels of fear and anger in conspiratorial news outlets' Facebook posts increase the engagement with these posts?

The three research questions examined in this dissertation are interdependent and work together to gain a full understanding of the role of fear and anger in the spread of belief in conspiracy theories. That is, if the presence of fear and anger increases the probability of an individual believing in a conspiracy theory then do conspiratorial news outlets utilise heightened levels of fear and anger in their messaging? Then, if conspiratorial news outlets utilise heightened levels of fear and anger in their Facebook posts and news headlines, does this influence the level of engagement these posts receive? Then, if heightened levels of fear and anger increase the engagement with conspiratorial news outlets Facebook posts. Then does the presence of fear and anger in conspiratorial messaging increase the probability of an individual believing in that conspiracy theory, and so on. The connected nature of the three research questions and their respective quantitative chapters is represented by Figure 5.1.

Figure 5.1: Dissertation Flowchart



The literature concerning the reasons behind individuals' conspiratorial beliefs has been suggestive that such a relationship exists. However, to date, no thorough analysis of the relationship has taken place. We know that one of the main psychological motives behind belief in conspiracy theories is the existential motive. That is, people like to feel safe and in control. The type of events that attract widespread conspiracy theories - pandemics, recessions, wars, terrorist attacks, elections etc. - leave people feeling vulnerable and not in control. Conspiracy theories are attractive in this situation as identifying those perpetrating the conspiracy which is making one feel out of control allows people to blame this feeling on another. While this motive may lead one down the conspiracy rabbit hole, there is little evidence to suggest belief in conspiracy theories actually satisfy this psychological motive (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). The political psychology literature has long understood that negative emotions such as fear and anger are particularly powerful in the opinion formation process because they leave a person with a sense of threat and that they are not in control (Brader & Marcus 2013). Therefore, the finding that fear and anger influence the cycle of conspiratorial belief fits into the theoretical expectations derived from the literature.

Further to the above expectations, the opinion formation process through which conspiratorial beliefs are developed bears a striking resemblance to the opinion formation process when in a heightened emotional state. Belief in conspiracy theories is associated with what is known as System 1 processes. This is form of opinion formation is characterised by a fast, automatic, and intuitive process. There is little time spent critically engaging with information. Rather it is quickly accepted (Douglas, Sutton & Cichocka 2017, Douglas et al. 2019, Douglas, Cichocka & Sutton 2020). Similarly, when we process information in a highly emotive state the emotion precedes conscious awareness. That is, the information is processed and the opinion is formed rapidly without time for critical analysis of the information. In a sense, this is from evolution. When we feel fearful it is because we sense danger. We must react and make decisions quickly when faced with direct danger. While one may not be facing any imminent danger when scrolling through Facebook, the information processing mechanism remains the same. Strikingly, the opinions formed via this process are particularly strong and difficult to change (Marcus 2003, Brader & Marcus 2013). The same mechanism has been observed with conspiracy belief (Sunstein & Vermeule 2009). Therefore, the two opinion formation processes are highly related to one another. This is suggestive that a relationship exists.

Through the research presented in this dissertation is unclear that fear and anger play a role in the formation and dissemination of conspiracy beliefs. This dissertation was unable to comprehensively prove that the presence of fear and anger influence individuals' perceptions of a conspiracy theory. The dissertation did demonstrate that conspiratorial outlets utilise heightened levels of fear and anger, and that heightened levels of fear and anger in conspiratorial news outlets' Facebook posts increase their engagement. It has been said several times in this dissertation that conspiracy theories are ubiquitous in American society. After the findings presented in this dissertation, it can be said that fear and anger are ubiquitous within conspiracy theories but the effect this has on conspiratorial beliefs is unclear.

Those concerned with the study of conspiracy theories have always known the dangers that widespread belief in these theories pose. Conspiratorial ideology is not the preoccupation of society's fringe. Most Americans believe in at least one conspiracy theory. These beliefs are incredibly harmful to the health of a democratic state and society in general. Belief in conspiracy theories increase partisanship, reduce public policy efficacy, political legitimacy, engagement in the political process, and institutional trust, harm public health, and increase the likelihood of political violence (Goertzel 1994, Byford 2011, Uscinski & Parent 2014, Bilewicz, Cichocka & Soral 2015, Cichocka, Marchlewska, Golec de

Zavala & Olechowski 2016, Brotherton 2015, Douglas et al. 2019).

For everyone, 2020 has brought these consequences to the forefront. Through varying conspiracy theories relating to Covid-19 and the 2020 Presidential Election, the democratic institutions of the United States have been undermined, public health policy during a global pandemic has been undermined, and political violence visited the Capitol. Strikingly, 147 Republicans, motivated by a conspiracy theory relating to Joe Biden's stealing of the 2020 US Presidential election, whether through genuine belief or political expediency, voted to overturn the democratic results of the 2020 Election (Yourish, Buchanan & Lu 2021). With such dangerous consequences understanding how conspiracy beliefs come to be held is of the utmost importance.

One of the main avenues of research concerned with misinformation, disinformation, and conspiracy theories is how to correct these views. We know that trying to correct individuals' conspiratorial beliefs often backfires. It can lead them to develop even stronger opinions and generally any effort to correct the incorrect theory is seen as part of the cover-up. For example, the 9/11 Commission was just part of the state covering up for its actions on that faithful September day. This is not necessarily unique to conspiracy theories. Evidence shows that retractions/corrective information across various topics is relatively ineffective. Indeed, from a psychological point of view, motivated reasoning tells us that most individuals seek out information that conforms to the opinions that they already hold and are likely to reject corrective information. Ultimately, the human ego does not like to be incorrect (Kunda 1990). However, this relationship seems particularly strong in the context of conspiracy theories. The literature has identified three successful ways in which misinformation. First, explicitly warning people that they may be about to be subjected to misinformation has been shown to reduce misinformed beliefs. Second, the counter-narrative should be repeated often. Thirdly, corrections should provide the actual account of what has occurred rather than merely stating that the misinformation is incorrect (Cook, Ecker & Lewandowsky 2015). While it is beyond the scope of this dissertation to provide new avenues towards correct misinformation and by extension conspiracy beliefs there is little doubt that the more we understand about how these opinions are formed the better able we will be to correct these erroneous opinions.

This dissertation is not without limitation. Chapter 2 examines the link between the presence of fear or anger in a conspiratorial article and belief in that conspiracy. The results presented were unable to comprehsnively demonstrate that this relationship exists and deserves further investigation. Chapters 3 and 4 examine the presence and effect of fear and anger in the Facebook posts, news articles, and news headlines written by conspiratorial news outlets. This is done instead of examining Facebook posts, news articles, and news headlines that are directly discussing a specific conspiracy theory. Ideally, content specifically relating to conspiracy theories would be examined. However, for the purposes of this dissertation, this was not possible for several reasons. First, conspiracy theories are by their very nature, clandestine, dynamic, and diverse. Therefore, in the case of the Facebook posts dataset (n = 7,221,509), identifying every post relating to a conspiracy theory would be very challenging if not impossible. In the case of the news article/headlines dataset (n = 180,175), the same applies. Perhaps, given the smaller sample size, human coding could be used. However, doing so using research assistants or crowdsourcing would be expensive. Further, given the clandestine and diverse nature of conspiracy theories, such a process would have the potential for human error. Creating an accurate and thorough way to identify conspiracy theories within text is beyond the scope of this dissertation. Indeed, it is perhaps a dissertation in and of itself. These issues are further compounded in the context of Facebook as many conspiracy theories (for example, anti-vaccine posts) may break Facebook's terms of use.

In these cases, such posts would be removed and therefore cannot be downloaded from Crowdtangle. This would also equate to a bias of omission with posts that did have exist on Facebook at one point not included in the sample.

Despite these limitations this dissertation ably identifies the role of fear and anger in conspiracy theorists' messaging. Indeed, there is a possibility that these limitations simply lead to the results presented understating the real relationship. Given the fact we can now see the influence that fear and anger have on conspiracy theories as well as the theoretical expectations arising from the literature, it would not be unsurprising for this relationship to be stronger in the context of posts specifically discussing conspiracy theories. Furthermore, non-conspiratorial news outlets may quote from conspiratorial sources (whether they be news outlets or individuals) thus amplifying the conspiratorial message. Finally, as discussed in detail in Chapter 1, 2020 was a unique year. A global pandemic occurred with many conspiracy theories surrounding its origins and the dangers it posed. Further, the President of the United States of America engaged in electoral fraud conspiracy theories with great regularity. Reporting from non-conspiratorial outlets on the pandemic itself, the related conspiracy theories, and the electoral fraud conspiracy theories quite possibly contained heightened levels of fear and anger. This is particularly relevant in the context of the pandemic with people genuinely frightened of the potential consequences of the Covid-19 virus. These may have diluted the usual differences between conspiratorial and non-conspiratorial outlets. Therefore, this dissertation and its limitations should be seen as a starting point for further study into the relationship between fear, anger, and the formation and dissemination of conspiracy theories.

Finally, it is important to stress the tangible opportunities for future research that this dissertation has created. First, this newly developed dataset of the entire population of Facebook posts created by the US-based news media can be used across a wide variety of political communication research. Utilising this dataset can assist scholars in the area of conspiracy theories and beyond. Second, the findings presented in Chapter 2 and Chapter 3 can be seen as a starting point for the study of the relationship between fear and anger, the belief in conspiracy theories, and the spread of conspiracy theories. As noted earlier, these chapters looked at the fear and anger within the Facebook posts created by conspiratorial news outlets rather than at posts that specifically reference a conspiracy theory. This is due to the difficulty that identifying very Facebook referencing a specific conspiracy poses, and the likelihood that this would lead to bias of omission. However, the findings presented in this dissertation suggest that fear and anger are used more by conspiratorial news outlets and this increases the interactions that these outlet's posts receive. As data processing and computing power continue to improve the ability to identify all posts relating to conspiracy theories becomes increasingly possible. This is the natural next step in this line of study. In doing so, the relationship between fear, anger, and conspiracy theories can be more conclusively understood. Therefore, the findings presented in this dissertation should be built upon. In doing so, we will gain an even deeper understanding of the role that fear and anger play in the formation and dissemination of conspirational beliefs.

Appendices

Appendix A

Chapter 2 Appendices

A.1 The Frames

Figure A.1: Neutral Frame

Deep State Proves that Americans Should be Afraid of their Government

The Herald Post
Sep 1, 2020, Thursday, Late Edition - Final
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Section: Section B; Column 3; Washington Desk; Pg. 23
Length: 552
Subheading: Deep state: Is there a secretive 'shadow government' working to undermine American Democracy?
Byline: By Thomas Headley, Political Editor
Dateline: EST

Body

There is the visible administration in Washington D.C. and then there is another more indefinable administration that is not explained in Civics 101 or observable to tourists at the White House or the Capitol. This 'Deep State' is a hybrid of national security and law agencies and various federal departments. This is a group of institutions connected to the federal justice system, Members of Congress, Wall Street, Silicon Valley, the Iveagh League, and military contractors. This state within a state is operating mostly in plain sight and acts mainly in the light of day, in accordance with its own interests with disregard to elected office.

The US legislation process is currently beset by gridlock with even basic legislation near impossible to pass. This is exemplified by the numerous budget impasses that have closed the federal state. Indeed, if one party controls even one house of Congress they can negate executive power. However, despite this apparent lack of power, US Presidents can liquidate American citizens without due process, detain people indefinitely without reason, conduct surveillance on the American people without judicial warrant, and engage in unprecedented investigations against federal employees. Within the United States, this power is characterized by massive displays of strength by federal and local law enforcement. Abroad, Presidents can start wars at will and engage in virtually any other activity whatsoever without so much as a by your leave from Congress. For instance, compelling the landing of a plane carrying the sovereign head of state over a foreign territory

These are not unusual instances, they have been so pervasive that they tend to be overlooked as background noise. In 2011, when political gridlock over the debt ceiling was halting the business of governance in Washington D.C., the United States somehow summoned the resources to topple Muammar Ghaddafi's regime in Libya and when the situation spilled over into Mali, provide assistance to the French intervention there. At a time when there was heated debate about continuing meat inspections and civilian air traffic control because of the budget the state was somehow able to commit $115 million to the situation in Syria.

The results of the Deep State's actions are not abstract as a tour of the cities of the Midwest and the situations in Iraq and Afghanistan will demonstrate. This is the consequence of the Washington Consensus. By way of example, since 2007 two bridges carrying interstate highways have given way due to a lack of funding for infrastructure, one resulting in 13 people passing away. At the same time the state spent $1.7 billion constructing a building in Utah that is the size of 17 football fields. This mammoth structure allows the state to store up to 500 quintillion pages of text. They need that much storage to track your electronic activity. Indeed, since 9-11, 33 facilities for top secret intelligence agencies have been built or are under construction. Combined they occupy the floor space of almost three Pentagons, about 17 million square feet, and yet Congress cannot fund the country's infrastructure.

Yes there is another state behind the one that is visible at either end of Pennsylvania Avenue, a hybrid entity of public and private institutions ruling the country according to its own interests and connected to, but only intermittently controlled by, the visible state whose leaders we choose.

Graphic

PHOTOS: The US State Capitol Building
Load-Date: Sep 8, 2020

Figure A.2: Anger Frame

Deep State Proves that Americans Should be Afraid of their Government

The Herald Post
Sep 1, 2020, Thursday, Late Edition - Final

Section: Section B; Column 3; Washington Desk; Pg. 23
Length: 580
Subheading: Deep state: Is there a secretive 'shadow government' working to undermine American Democracy?
Byline: By Thomas Headley, Political Editor
Dateline: EST

Body

There is the visible government in Washington D.C. and then there is another that is not explained in Civics 101 or observable to tourists at the White House or the Capitol. This 'Deep State' is a hybrid of national security and law enforcement agencies as well as various federal departments. This is a group of institutions connected through threads of money and greed to the federal justice system, Members of Congress, Wall Street, Silicon Valley, the Ivy League, and military contractors. This state within a state is operating mostly in plain sight and acts mainly in the light of day, in accordance with its own interests with disregard to elected office.

US politics is currently beset by gridlock, with passing even basic legislation almost unattainable. This is exemplified by the numerous budget standoffs that have closed the federal state. However, despite this apparent impotence, US Presidents can murder American citizens without regard for due process, effectively kidnap people without charge, conduct illicit surveillance on the American people without judicial warrant, and engage in the unlawful persecution of federal employees. Within the United States, this power is characterized by brazen and furious displays of callous brutality and the contemptible use of martial law by federal and local police. Abroad, Presidents can start conflict at will and engage in virtually any other destructive activity whatsoever without so much as a by your leave from Congress. For instance, arranging the forced landing of a plane carrying the sovereign head of a state over foreign territory.

These are not unusual instances, they have been so pervasive that they tend to be disregarded as background noise. In 2011, when political warfare over the debt ceiling was paralyzing the business of governance in Washington D.C., the United States somehow summoned the resources to overthrow Muammar Ghaddafi's regime in Libya and when the destruction created by the fighting spilt over into Mali, provide blatant assistance to the French effort there. At a time when there was heated debate about continuing meat inspections and civilian air traffic control because of the budget crisis, the US was somehow able to commit $115 million to the conflict in Syria.

The results of the Deep State's actions are not abstract as a tour of the miserable and crime-ridden cities of the Midwest and the chaotic conflicts in Iraq and Afghanistan will attest. This is the consequence of the Washington Consensus. By way of example, since 2007 two bridges carrying interstate highways have been destroyed due to the lack of funding for infrastructure, one slaying 13 people. In essence, a lack of funding condemned these bridges to being accidentally demolished. At the same time, the state spent $1.7 billion constructing a building in Utah that is the size of 17 football fields. This loathsome structure serves to allow the state to store up to 500 quintillion pages of text. They need that much storage to pry on your electronic activity. Indeed, since 9-11, 33 facilities for top-secret federal agencies have been built or are under construction. Combined they occupy the floor space of almost three Pentagons, or about 17 million square feet, and yet they cannot fund the turnaround of the country's miserable infrastructure.

Yes, there is another state behind the one that is visible at either end of Pennsylvania Avenue, a hybrid entity of public and private institutions deceiving the country according to its own interests and connected to, but only intermittently controlled by, the visible government whose leaders we choose.

Graphic

PHOTOS: The US State Capitol Building
Load-Date: Sep 8, 2020

Figure A.3: Fear Frame

Deep State Proves that Americans Should be Afraid of their Government

The Herald Post
Sep 1, 2020, Thursday, Late Edition - Final

Section: Section B; Column 3; Washington Desk; Pg. 23
Length: 583
Subheading: Deep state: Is there a secretive 'shadow government' working to undermine American Democracy?
Byline: By Thomas Headley, Political Editor
Dateline: EST

Body

There is the visible government in Washington D.C. and then there is another more shady government that is not explained in Civics 101 or observable to tourists at the White House or the Capitol. This 'Deep State' is a hybrid of national security and law enforcement agencies as well as various federal departments. This is a group of institutions connected through threads of money and ambition to the federal justice system, Members of Congress, Wall Street, Silicon Valley, the Ivy League, and military contractors. This state within a state is hiding mostly in plain sight and acts mainly in the light of day, and in accordance with its own interests with contempt for elected office.

US politics is currently beset by gridlock, with passing even basic legislation near hopeless. This is exemplified by the numerous budget standoffs that have closed the Federal Government. Indeed, if one party controls even one branch of government they can quash executive power. However despite this apparent impotence, US Presidents can kill American citizens with contempt for due process, effectively kidnap people without charge, conduct illicit surveillance on the American people without judicial warrant, and engage in the unlawful persecution of federal employees. Within the United States, this power is characterized by frightening displays of intimidating force by a militarized federal and local police force. Abroad, Presidents can start wars at will and engage in virtually any other lethal activity whatsoever without so much as a by your leave from Congress. For instance, arranging the forced landing of a plane carrying the sovereign head of state over a foreign territory.

These are not isolated instances, they have been so pervasive that they tend to be disregarded as background noise. In 2011, when political warfare over the debt ceiling was paralyzing the business of governance in Washington D.C., the United States government somehow summoned the resources to overthrow Muammar Ghaddafi's regime in Libya and when the instability created by that war spilt over into Mali, provide overt and covert military assistance to French war effort there. At a time when there was heated debate about continuing meat inspections and civilian air traffic control because of the budget crisis the US government was somehow able to commit $115 million to the civil war in Syria.

The results of the Deep State's actions are not abstract, as a tour of the decaying and bankrupt cities of the Midwest and the wars in Iraq and Afghanistan will attest. This is the consequence of the Washington Consensus. By way of example, since 2007 two bridges carrying interstate highways have collapsed due to scarce funding for infrastructure, one killing 13 people. At the same time, the government spent $1.7 billion constructing a building in Utah that is the size of 17 football fields. This mammoth structure serves to allow the government to store up to 500 quintillion pages of text. They need that much storage to stalk your electronic activity. Indeed, since 9-11, 33 facilities for top secret government agencies have been built or are under construction. Combined they occupy the floor space of almost three Pentagons, about 17 million square feet, and yet the government cannot fund the turnaround of the country's infrastructural rot.

Yes, there is another government concealed behind the one that is visible at either end of Pennsylvania Avenue, a hybrid entity of public and private institutions ruling the country according to its own interests and connected to, but only intermittently controlled by, the visible government whose leaders we choose.

Graphic

PHOTOS: The US State Capitol Building
Load-Date: Sep 8, 2020

Figure A.4: Control Frame

Low Rainfall in US Midwest Drives Corn Prices Higher

The Herald Post
Sep 1, 2020, Thursday, Late Edition - Final

Section: Section B; Column 3; Washington Desk; Pg. 23
Length: 534
Subheading: Benchmark up almost 4% since start of week as sweltering heat hits crop conditions
Byline: By Thomas Headley, Political Editor
Dateline: EST

Body

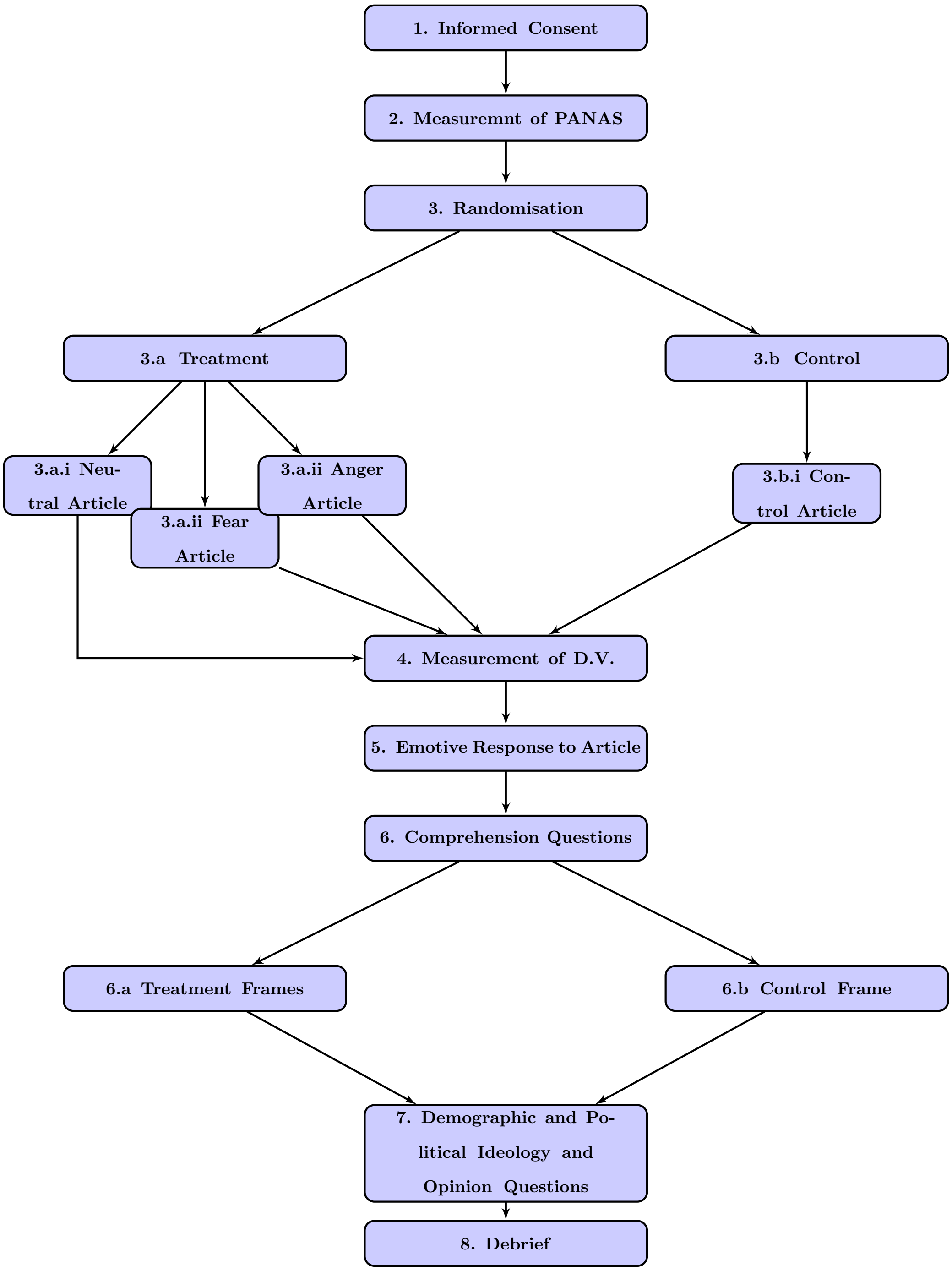
Worries about a lack of rainfall this month in the US Midwest have lifted corn prices, with data from the US Department of Agriculture pointing to deteriorating crop conditions. Benchmark corn prices are up almost 4 per cent since the start of the week at $3.39¼ a bushel, and have gained 9 per cent over the past two weeks. Prices had already received a boost after crops were damaged during a storm on August 10 that hit Iowa, a key corn-growing state. The latest concern, however, has been the low rainfall in the US corn belt throughout August, a situation that is expected to continue for the rest of the week. “[The] forecast remains hot and sweltering for the balance of the week,” said Matt Ammerman at commodity brokers Stone X. He added that while conditions were set to become cooler by the weekend, the lack of rain was likely to lead to a further decline in crop conditions. Farmers have been hoping that Hurricane Laura might bring in the much-needed rain in the Midwest. However, the immediate forecast for the region is that it will remain dry. “It’s a non-issue,” said Mr Ammerman. Much of the corn crop has nearly reached maturity, but the plants still need moisture for the final stages. With parts of the Midwest receiving only 15 to 40 per cent of normal rainfall, the crop will need to rely on existing soil moisture, which was likely to affect yields, said Stone X

According to the USDA’s latest weekly crop progress report, the percentage of corn crops classed as good to excellent dropped to 64 per cent from 69 per cent in the previous week. In Iowa, it fell to 50 per cent from 59 per cent, reflecting the effects of the storm. The weather concerns come as meteorological agencies in the US and Australia have recently raised the likelihood of a La Niña weather phenomenon occurring later this year. A La Niña, caused by the cooling of the tropical Pacific Ocean, typically brings droughts to the US Midwest and California. Commodity data firm Gro Intelligence said that while its full impact could not be predicted, “history has shown that the consequences of such climate events can be far-reaching”. During the 2012 La Niña, the US suffered its worst drought in 50 years and grain and soyabean prices surged. However, the last La Niña in 2017 was weak and had little impact on commodity markets. La Niña also brings lack of rain in southern Brazil and central Argentina, and farmers and traders in Argentina are bracing for a drought because the country has already been experiencing lower than average rains. Meanwhile, uncertainty over the demand outlook continues because of the coronavirus pandemic and the US-China trade war. So far, active buying of grains and soyabeans by China has been supporting prices despite the geopolitical tensions. Beijing has increased its purchases of US agricultural crops considerably in recent weeks, which will also be reflected after some delay in US export figures, said Commerzbank. Soyabean prices in Chicago have risen 3.7 per cent over the past two weeks to $9.11¼ a bushel while wheat is up 7.3 per cent to $5.31 1/2.

Graphic

PHOTOS: The US State Capitol Building
Load-Date: Sep 8, 2020

A.2 Experiment Design Flowchart



A.3 Framing Experiment Questions

Measurement of PANAS[1]

During the past 30 days, how much of the time did you feel...	None of the time	A little of the time	Some of the time	Most of the time	All of the time
...so sad nothing could cheer you up?	-	-	-	-	-
...nervous?	-	-	-	-	-
...restless or fidgety?	-	-	-	-	-
...hopeless?	-	-	-	-	-
...that everything was an effort?	-	-	-	-	-
...worthless?	-	-	-	-	-
..cheerful?	-	-	-	-	-
...in good spirits	-	-	-	-	-
...extremely happy?	-	-	-	-	-
...calm and peaceful?	-	-	-	-	-
...satisfied?	-	-	-	-	-
...full of life?	-	-	-	-	-

A.3.1 Measurement of the Dependent Variable

To what extent do you agree with the following statement: "A shadow government, known as the 'Deep State' controls American society?"

- Strongly agree
- Agree
- Somewhat agree
- Neither agree nor disagree
- Somewhat disagree
- Disagree
- Neither agree nor disagree

[1]The numbers refer to each sections placement on the flow chart in Appendix A.2

5. Emotive Response to Article

On a scale of 0-10 (with 1 being the lowest and 10 being the highest) how does the article make you feel?	1	2	3	4	5	5	7	8	9	10
Enthusiasm	-	-	-	-	-	-	-	-	-	-
Sadness		-	-	-	-	-	-	-	-	- -
Fear	-	-	-	-	-	-	-	-	-	-
Calmness	-	-	-	-	-	-	-	-	-	-
Anger	-	-	-	-	-	-	-	-	-	-
Disgust	-	-	-	-	-	-	-	-	-	-
Shame	-	-	-	-	-	-	-	-	-	-

6. Comprehension Questions

6.a Treatment Frames

- How much did the US Government spend on the building in Utah?
  - $500 million
  - $1.7 billion
  - $2.3 billion
  - $5 billion
  - $3.6 billion
- How many people died due to the two bridge collapses in 2007?
  - 23
  - 47
  - 8
  - 13
  - 31
- True or False: The building in Utah is the size of 23 football fields.
  - True

  - False

- True or False: The new servers allow the NSA to store up to 500 quintillion pages of text.
  - True
  - False

6.b Control Frame

- True or False: Low rainfall in the US Midwest has led to a rise in the price of corn.
  - True
  - False
- Which of the following is a key corn-growing state?
  - California
  - Iowa
  - Florida
  - Colorado
  - Kentucky
- Matt Ammerman works for which commodity broker?
  - Goldman Sachs
  - JP Morgan Chase
  - Stone X
  - Morgan Stanley
  - The Chicago Board of Trade

- True or False: The likelihood of a La Nińa weather phenomenon occurring later this year has decreased.
  - True
  - False

7. Demographic and Political Ideology and Opinion Questions

- What is your gender?
  - Male
  - Female
  - Other
  - Prefer not to say
- What is your age?
- If the Presidential Election were held today, which candidate would you vote for?
  - Donald Trump **(R)**
  - Joe Biden **(D)**
  - Third Party
  - Don't know/no preference
  - Would not vote
- Are you an American citizen?
  - Yes
  - No
- What race are you?
  - White

  - Black or African American
  - Hispanic
  - American Indian or Alaska Native
  - Asian
  - Native Hawaiian
  - Other

- Which of the following best describes your present situation with regard to employment?
  - Employed full time
  - Employed part time
  - Unemployed looking for work
  - Unemployed not looking for work
  - Retired
  - Student
  - Disabled

- What is the highest level of education that you have achieved?
  - Less than high school
  - High school graduate
  - Some college
  - 2 year degree
  - 4 year degree
  - Professional degree
  - Master's degree or equivalent
  - Doctorate

- To what extent do you agree with the following statement: "I am religious."?
  - Strongly agree
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
  - Neither agree nor disagree
- To what extent do you agree with the following statement: "I identify with the scientific worldview."?
  - Strongly agree
  - Agree
  - Somewhat agree
  - Neither agree nor disagree
  - Somewhat disagree
  - Disagree
  - Neither agree nor disagree
- What is the highest level of education achieved by your mother (or stepmother or female guardian)?
  - Less than high school
  - High school graduate
  - Some college
  - 2 year degree

  - 4 year degree
  - Professional degree
  - Master's degree or equivalent
  - Doctorate

- What kind of work does your mother (or stepmother or female guardian) do for her main job? If your mother is not working now think about the last job she had.

- What is the highest level of education achieved by your father (or stepfather or male guardian)?

  - Less than high school
  - High school graduate
  - Some college
  - 2 year degree
  - 4 year degree
  - Professional degree
  - Master's degree or equivalent
  - Doctorate

- What kind of work does your father (or stepfather or male guardian) do for her main job? If your father is not working now think about the last job he had.

- Activism and Radicalism Intention Scales (ARIS):

Please think of a political or social cause that you consider of great importance. To what extent do you agree with the following statements? This cause can be political, social, economic, or cultural in nature. Keep this cause in mind as you answer the following questions.	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I would join/belong to an organization that fights for my cause's political and legal rights	-	-	-	-	-	-	-
I would donate money to an organization that fights for my cause's political and legal rights	-	-	-	-	-	-	-
I would volunteer my time working (i.e. write petitions, distribute flyers, recruit people, etc.) for an organization that fights for my cause's political and legal rights	-	-	-	-	-	-	-
I would travel for one hour to join in a public rally, protest, or demonstration in support of my cause	-	-	-	-	-	-	-
I would continue to support an organization that fights for my cause's political and legal rights even if the organization sometimes breaks the law	-	-	-	-	-	-	-
I would continue to support an organization that fights for my cause's political and legal rights even if the organization sometimes resorts to violence	-	-	-	-	-	-	-
I would participate in a public protest in support of my cause even if I thought the protest might turn violent	-	-	-	-	-	-	-
I would attack police or security forces if I saw them beating members because they share the same cause as me	-	-	-	-	-	-	-
I would go to war to protect and/or further my cause	-	-	-	-	-	-	-
I would retaliate against members of a group that had attacked my group, even if I couldn't be sure I was retaliating against the guilty parties	-	-	-	-	-	-	-

- Conspiratorial Predisposition:

To what extent do you agree with the following statements?	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Big events like wars, recessions, and the outcome of elections are controlled by a small group of people working in secret against us	-	-	-	-	-	-	-
The people that really run the country are not known to the voters	-	-	-	-	-	-	-
Even though we live in a democracy a few people will always run things anyway	-	-	-	-	-	-	-
Most of our lives are controlled by plots hatched in secret places.	-	-	-	-	-	-	-

- Need for Chaos:

- How interesting would you say politics is?

  - Extremely interesting
  - Very interesting
  - Moderately interesting

To what extent do you agree with the following statements?	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I fantasize about a natural disaster wiping out most of humanity such that a small group of people can start all over.	-	-	-	-	-	-	-
I think society should be burned to the ground.	-	-	-	-	-	-	-
When I think about our political and social institutions, I cannot help thinking "just let them all burn."	-	-	-	-	-	-	-
We cannot fix the problems in our social institutions, we need to tear them down and start over.	-	-	-	-	-	-	-
Sometimes I just feel like destroying beautiful things.							

  - Slightly interesting
  - Not interesting at all

- Are you registered to any of the following political parties?
  - Republican Party
  - Democratic Party
  - The Libertarian Party
  - The Green Party
  - Other
  - No Registration

- Are you registered to any of the following political parties?
  - Republican Party
  - Democratic Party
  - Third Party
  - Don't know/no preference
  - Would not vote

A.4 Overview of Variables

Table A.1: Positive and Negative Affect Schedule

Variable	Regression Equation Code	Measurement
Belief in deep state conspiracy theory	-	7 point Likert scale
Willingness to share deep state conspiracy theory	-	5 point Likert scale
Fear	fear	Coded as 1 if exposed to fear treatment
Anger	anger	Coded as 1 if exposed to fear treatment
Gender	gender	Coded as 1 if male
Age	age	Coded in decade intervals. 18-24 coded as 1 & 65-74 coded as 6
Race	race	Coded as 1 if white
Employment	emp	Coded as 1 if in full-time employment
Education	educ	Highest level of education received. Ranging from "Less than High School' (coded as 1) to Doctorate (coded as 8)
Female guardian education	educ	Highest level of education received. Ranging from "Less than High School' (coded as 1) to Doctorate (coded as 8)
Male guardian education	educ	Highest level of education received. Ranging from "Less than High School' (coded as 1) to Doctorate (coded as 8)
Party registration	reg	Coded as 1 if a registered Republican
Political interest	polint	5 point Likert scale
Religiosity	relig	7 point Likert scale to the statement: "I am religious" ranging from strongly disagree to strongly agree
Scientific worldview	scien	7 point Likert scale to the statement: "I identify with the scientific worldview" ranging from strongly disagree to strongly agree
Conspiratorial Outlook (principal)	consppc	4 questions combined using principal component analysis
ARIS radical principal	arisradicalpc	4 questions combined using principal component analysis
ARIS participation principal	arisparticippc	10 questions combined using principal component analysis
PANAS positive principal	panaspospc	12 questions combined using principal component analysis
PANAS negative principal	panasnegpc	12 questions combined using principal component analysis
Conspiratorial Outlook (factor)	conspfactor	4 questions combined using factor analysis
ARIS (factor)	arisfactor	10 questions combined using factor analysis
PANAS positive (factor)l	panasposfactor	12 questions combined using factor analysis
PANAS negative (factor)l	panasnegfactor	12 questions combined using factor analysis

Table A.2: Positive and Negative Affect Schedule

During the past 30 days, how much of the time did you feel...	None of the time (n)	A little of the time (n)	Some of the time (n)	Most of the time (n)	All of the time (n)
...so sad nothing could cheer you up?	879	327	234	106	49
...nervous?	425	574	320	206	70
...restless or fidgety?	446	548	357	199	45
...hopeless?	768	389	232	144	62
...that everything was an effort?	452	442	364	244	93
...worthless?	906	316	184	132	57
..cheerful?	111	347	501	518	118
...in good spirits	72	293	433	662	135
...extremely happy?	338	401	456	317	83
...calm and peaceful?	78	289	483	602	151
...satisfied?	107	309	499	558	129
...full of life?	182	353	477	457	126

Table A.3: Emotional Response to Frame

On a scale of 0-10 (with 1 being the lowest and 10 being the highest) how does the article make you feel?	1 (n)	2 (n)	3 (n)	4 (n)	5 (n)	5 (n)	7 (n)	8 (n)	9 (n)	10 (n)
Enthusiasm	989	211	95	66	64	53	35	36	30	15
Sadness	451	192	170	137	151	133	113	106	70	69
Fear	559	238	161	111	118	123	99	71	68	45
Calmness	668	214	133	100	159	129	58	50	41	42
Anger	458	203	162	129	137	132	107	108	64	93
Disgust	449	179	138	98	124	130	119	114	100	143
Shame	826	197	121	84	87	84	69	47	39	39

Table A.4: Activism and Radicalism Intention Scales

Please think of a political or social cause that you consider of great importance. To what extent do you agree with the following statements? This cause can be political, social, economic, or cultural in nature. Keep this cause in mind as you answer the following questions.	Strongly agree (n)	Agree (n)	Somewhat agree (n)	Neither agree nor disagree (n)	Somewhat disagree (n)	Disagree (n)	Strongly disagree (n)
I would join/belong to an organization that fights for my cause's political and legal rights	58	70	154	305	437	374	196
I would donate money to an organization that fights for my cause's political and legal rights	84	71	180	258	441	358	202
I would volunteer my time working (i.e. write petitions, distribute flyers, recruit people, etc.) for an organization that fights for my cause's political and legal rights	93	76	238	328	416	294	149
I would travel for one hour to join in a public rally, protest, or demonstration in support of my cause	175	156	339	305	283	214	122
I would continue to support an organization that fights for my cause's political and legal rights even if the organization sometimes breaks the law	323	217	289	324	225	159	57
I would continue to support an organization that fights for my cause's political and legal rights even if the organization sometimes resorts to violence	499	224	279	236	183	110	63
I would participate in a public protest in support of my cause even if I thought the protest might turn violent	499	234	309	211	180	110	51
I would attack police or security forces if I saw them beating members because they share the same cause as me	641	228	254	212	129	83	45
I would go to war to protect and/or further my cause	479	216	247	319	169	94	70
I would retaliate against members of a group that had attacked my group, even if I couldn't be sure I was retaliating against the guilty parties	632	264	265	204	117	76	36

A.5 Full Ordinary Least Squares Results

This section contains the full OLS regression results for Chapter 2. The literature identifies several '*response validity indicators*'. Namely: (1) lack of comprehension responses; (2) too quick response; (3) response inconsistency; (4) straightlining, statistically improbable responses; (5) disqualified responses; and (6) unusual comments (Greszki, Meyer & Schoen 2014, Chmielewski & Kucker 2020). When there are high levels of these indicators the quality and validity of data can be affected. This would undermine any results returned.

- **Iteration 1:**
- **Iteration 2:**
- **Iteration 3:**
- **Iteration 4:**
- **Iteration 5:**

Table A.5: Model 1 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Exposure	0.806	0.798	0.810	0.823	0.815
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.6: Model 2 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Exposure	0.643	0.640	0.651	0.651	0.674
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	−0.308	−0.316	−0.317	−0.314	−0.287
	(0.001)	(0.002)	(0.001)	0.001	(0.003)
White	−0.238	−0.156	−0.236	−0.200	−0.219
	(0.025)	(0.166)	(0.027)	(0.065)	(0.048)
Employment Status	−0.035	−0.012	−0.034	−0.018	−0.046
	(0.721)	(0.909)	(0.727)	(0.854)	(0.646)
Education Level	−0.377	−0.349	−0.366	−0.377	−0.398
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)
Religiosity	0.128	0.130	0.124	0.132	0.129
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldview	−0.278	−0.298	−0.282	−0.291	−0.284
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.430	0.412	0.450	0.426	0.398
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{principal}$	0.038	0.044	0.039	0.033	0.037
	(0.094)	(0.075)	(0.085)	(0.151)	(0.115)
Mild Political Engagement $_{principal}$	−0.064	−0.067	−0.066	−0.051	−0.055
	(0.055)	(0.060)	(0.048)	(0.130)	(0.105)
Positive PANAS $_{principal}$	−0.009	−0.002	−0.009	−0.009	−0.010
	(0.645)	(0.910)	(0.646)	(0.639)	(0.606)
Negative PANAS $_{principal}$	0.186	0.173	0.186	0.188	0.207
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Need for Chaos Positive PANAS $_{principal}$	0.202	0.194	0.202	0.210	0.200
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.7: Model 3 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Exposure	0.644	0.641	0.651	0.651	0.675
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	−0.308	−0.317	−0.317	−0.313	−0.286
	(0.001)	(0.002)	(0.000)	(0.001)	(0.003)
White	−0.241	−0.161	−0.238	−0.202	−0.220
	(0.024)	(0.156)	(0.025)	(0.061)	(0.048)
Employment Status	−0.034	−0.011	−0.033	−0.017	−0.044
	(0.731)	(0.913)	(0.737)	(0.862)	(0.660)
Education Level	−0.373	−0.345	−0.363	−0.374	−0.394
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Religiosity	0.129	0.132	0.126	0.134	0.131
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldview	−0.278	−0.297	−0.280	−0.290	−0.283
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.432	0.412	0.451	0.427	0.399
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative PANAS $_{factor}$	−0.024	−0.007	−0.024	−0.025	−0.028
	(0.609)	(0.887)	(0.609)	(0.604)	(0.570)
Positive PANAS $_{factor}$	0.314	0.289	0.313	0.318	0.349
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{factor}$	0.099	0.113	0.102	0.087	0.097
	(0.070)	(0.055)	(0.062)	(0.117)	(0.088)
Mild Political Engagement $_{factor}$	−0.106	−0.112	−0.109	−0.086	−0.092
	(0.045)	(0.047)	(0.039)	(0.109)	(0.090)
Need for Chaos Positive PANAS $_{factor}$	0.392	0.372	0.391	0.407	0.383
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.8: Model 4 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Emotion	0.218	0.265	0.220	0.213	0.183
	(0.064)	(0.038)	(0.063)	(0.078)	(0.136)
Control	−0.672	−0.639	−0.677	−0.691	−0.707
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.9: Model 5 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Emotion	0.247	0.282	0.243	0.238	0.181
	(0.020)	(0.015)	(0.023)	(0.028)	(0.103)
Control	−0.479	−0.453	−0.490	−0.496	−0.556
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	−0.309	−0.321	−0.317	−0.321	−0.293
	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
Age	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.768)	(0.710)	(0.769)	(0.713)	(0.693)
White	−0.227	−0.156	−0.224	−0.194	−0.216
	(0.033)	(0.168)	(0.036)	(0.074)	(0.052)
Employment Status	−0.036	−0.009	−0.035	−0.019	−0.049
	(0.713)	(0.929)	(0.719)	(0.849)	(0.631)
Education Level	−0.379	−0.356	−0.368	−0.378	−0.398
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Religiosity	0.127	0.131	0.124	0.132	0.129
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldview	−0.276	−0.293	−0.280	−0.289	−0.280
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.428	0.411	0.448	0.422	0.398
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{principal}$	0.034	0.041	0.034	0.031	0.036
	(0.143)	(0.099)	(0.133)	(0.182)	(0.131)
Mild Political Engagement $_{principal}$	−0.063	−0.068	−0.064	−0.053	−0.057
	(0.060)	(0.056)	(0.054)	(0.123)	(0.095)
Positive PANAS $_{principal}$	−0.009	−0.002	−0.009	−0.007	−0.009
	(0.642)	(0.929)	(0.644)	(0.697)	(0.634)
Negative PANAS $_{principal}$	0.188	0.178	0.188	0.191	0.209
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Need for Chaos Positive PANAS $_{principal}$	0.203	0.192	0.204	0.208	0.197
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.10: Model 6 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Emotion	0.245	0.279	0.240	0.235	0.178
	(0.022)	(0.017)	(0.025)	(0.031)	(0.110)
Control	−0.483	−0.457	−0.494	−0.499	−0.560
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	−0.309	−0.323	−0.317	−0.320	−0.293
	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
Age	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.770)	(0.713)	(0.770)	(0.715)	(0.699)
White	−0.230	−0.161	−0.227	−0.198	−0.218
	(0.031)	(0.157)	(0.034)	(0.070)	(0.051)
Employment Status	−0.036	−0.009	−0.035	−0.019	−0.048
	(0.717)	(0.929)	(0.724)	(0.853)	(0.640)
Education Status	−0.374	−0.352	−0.364	−0.374	−0.393
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Religiosity	0.129	0.132	0.126	0.133	0.131
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldview	−0.276	−0.293	−0.279	−0.288	−0.279
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.432	0.412	0.451	0.425	0.401
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative PANAS $_{factor}$	−0.024	−0.005	−0.024	−0.020	−0.025
	(0.617)	(0.914)	(0.616)	(0.672)	(0.607)
Positive PANAS $_{factor}$	0.317	0.297	0.316	0.322	0.351
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{factor}$	0.088	0.107	0.091	0.082	0.095
	(0.108)	(0.070)	(0.097)	(0.142)	(0.098)
Mild Political Engagement $_{factor}$	−0.104	−0.115	−0.108	−0.089	−0.095
	(0.049)	(0.043)	(0.043)	(0.103)	(0.079)
Need for Chaos Positive PANAS $_{factor}$	0.395	0.368	0.394	0.404	0.378
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.11: Model 7 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Fear	0.217	0.271	0.216	0.219	0.196
	(0.113)	(0.068)	(0.116)	(0.117)	(0.168)
Anger	0.220	0.259	0.223	0.206	0.170
	(0.109)	(0.080)	(0.104)	(0.142)	(0.231)
Control	−0.672	−0.639	−0.677	−0.691	−0.707
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.12: Model 8 OLS Regression Results Minus

	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Fear	0.249	0.274	0.238	0.250	0.186
	(0.044)	(0.041)	(0.055)	(0.047)	(0.150)
Anger	0.245	0.290	0.249	0.225	0.177
	(0.047)	(0.031)	(0.046)	(0.074)	(0.171)
Control	−0.479	−0.453	−0.490	−0.496	−0.557
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	−0.309	−0.320	−0.316	−0.321	−0.293
	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)
Age	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.767)	(0.714)	(0.772)	(0.707)	(0.691)
White	−0.227	−0.156	−0.224	−0.194	−0.217
	(0.033)	(0.169)	(0.036)	(0.073)	(0.052)
Employment Status	−0.036	−0.009	−0.035	−0.019	−0.049
	(0.713)	(0.930)	(0.720)	(0.850)	(0.630)
Education Level	−0.378	−0.356	−0.368	−0.378	−0.397
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Religiosity	0.127	0.131	0.124	0.132	0.129
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldviews	−0.276	−0.293	−0.280	−0.288	−0.280
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.428	0.411	0.448	0.422	0.398
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{principal}$	0.034	0.041	0.034	0.031	0.036
	(0.143)	(0.099)	(0.134)	(0.180)	(0.131)
Mild Political Engagement $_{principal}$	−0.063	−0.068	−0.064	−0.053	−0.057
	(0.061)	(0.058)	(0.055)	(0.122)	(0.095)
Positive PANAS $_{principal}$	−0.009	−0.002	−0.009	−0.007	−0.009
	(0.643)	(0.926)	(0.644)	(0.698)	(0.634)
Negative PANAS $_{principal}$	0.188	0.178	0.188	0.191	0.209
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Need for Chaos Positive PANAS $_{principal}$	0.203	0.192	0.204	0.208	0.197
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

Table A.13: Model 9 OLS Regression Results Minus

	Iteration 1	**Iteration 2**	**Iteration 3**	**Iteration 4**	**Iteration 5**
Fear	0.247	0.272	0.235	0.247	0.183
	(0.047)	(0.044)	(0.058)	(0.050)	(0.158)
Anger	0.243	0.285	0.245	0.222	0.174
	(0.050)	(0.035)	(0.049)	(0.080)	(0.181)
Control	−0.483	−0.457	−0.494	−0.499	−0.560
	(0.000)	(0.000)	(0.000)	(0.000)	0.00002
Male	−0.310	−0.322	−0.317	−0.320	−0.293
	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)
Age	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.769)	(0.716)	(0.772)	(0.709)	(0.698)
White	−0.230	−0.160	−0.227	−0.198	−0.219
	(0.032)	(0.158)	(0.034)	(0.069)	(0.051)
Employment Status	−0.036	−0.009	−0.035	−0.019	−0.048
	(0.717)	(0.930)	(0.725)	(0.853)	(0.639)
Education Level	−0.374	−0.352	−0.364	−0.374	−0.393
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Religiosity	0.129	0.132	0.125	0.133	0.131
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Scientific Worldview	−0.276	−0.293	−0.279	−0.287	−0.279
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Registered Republican	0.431	0.412	0.451	0.424	0.401
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Negative PANAS $_{factor}$	−0.024	−0.006	−0.024	−0.020	−0.025
	(0.618)	(0.913)	(0.616)	(0.673)	(0.607)
Positive PANAS $_{factor}$	0.317	0.297	0.316	0.322	0.350
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme Political Engagement $_{factor}$	0.088	0.107	0.091	0.082	0.095
	(0.108)	(0.071)	(0.097)	(0.140)	(0.098)
Mild Political Engagement $_{factor}$	−0.105	−0.114	−0.107	−0.089	−0.096
	(0.049)	(0.044)	(0.044)	(0.101)	(0.079)
Need for Chaos Positive PANAS $_{factor}$	0.395	0.368	0.394	0.404	0.378
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in parentheses

A.6 Ordinal Logistic Regression Results

Table A.14: Ordinal Logistic Regression Results

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
Exposure	0.758	0.673	0.672						
	(0.000)	(0.000)	*						
Emotion				0.206	0.254	0.249			
				(0.055)	(0.021)	(0.023)			
Fear							0.213	0.249	0.246
								(0.050)	(0.054)
Anger							0.200	0.258	0.253
							(0.107)	(0.042)	(0.046)
Control				−0.624	−0.507	−0.509	−0.624	−0.507	−0.509
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male		−0.313	−0.310		−0.313	−0.311		−0.312	−0.310
		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Age		−0.0001	−0.0001		−0.0002	−0.0002		−0.0002	−0.0002
		(0.863)	(0.870)		(0.832)	(0.839)		(0.835)	(0.841)
White		−0.229	−0.230		−0.222	−0.224		−0.222	−0.224
		0.038	0.036		0.044	0.042		0.044	0.042
Employment Status		0.001	0.003		0.001	0.003		0.001	0.003
		(0.992)	(0.977)		(0.991)	(0.975)		(0.990)	(0.974)
Education Level		−0.379	−0.374		−0.380	−0.375		−0.380	−0.375
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Religiosity		0.132	0.133		0.132	0.133		0.132	0.133
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Scientific Worldviews=		−0.280	−0.279		−0.281	−0.280		−0.282	−0.280
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Registered Republican		0.436	0.437		0.431	0.433		0.432	0.433
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Extreme Political Engagement $_{principal}$		0.034			0.034			0.034	
		(0.162)			(0.164)			(0.164)	
Mild Political Engagement $_{principal}$		−0.053			−0.054			−0.054	
		(0.123)			(0.115)			(0.116)	
Positive PANAS $_{principal}$		−0.020			−0.019			−0.019	
		(0.302)			(0.343)			(0.343)	
Negative PANAS $_{principal}$		0.187			0.191			0.191	
		(0.000)			(0.000)			(0.000)	
Need for Chaos Positive PANAS $_{principal}$		0.207			0.206			0.206	
		(0.000)			(0.000)			(0.000)	
Negative PANAS $_{factor}$			−0.054			−0.050			−0.050
			(0.283)			(0.324)			(0.324)
Positive PANAS $_{factor}$			0.316			0.323			0.323
			(0.000)			(0.000)			(0.000)
Extreme Political Engagement $_{factor}$			0.090			0.090			0.090
			(0.122)			(0.122)			(0.122)
Mild Political Engagement $_{factor}$			−0.089			−0.091			−0.091
			(0.103)			(0.095)			(0.097)
Need for Chaos Positive PANAS $_{factor}$			0.398			0.396			0.396
			(0.000)			(0.000)			(0.000)

Note: p-values in parentheses

Appendix B

Chapter 3 Appendices

B.1 Dataset Summary Statistics

Table B.1: Facebook Dataset Summary Statistics

Variable	N	Mean	St.Dev	Minimum	Maximum
Overperform	7,221,509	-6.153206	24.98127	-978.61	997.2
Fear	7,221,509	8.361679	11.81994	0	100
Anger	7,221,509	5.582767	8.940884	0	100
Ideological Bias	7,221,509	3.813395		1	7
Standard of Reporting	7,221,509	4.484117	.9151486	1	6
Likes at Posting	7,221,509	1763839	3538846	1	34,300,000
Presidential Election	7,221,509	.0450712	.0654406	.0006406	.9074733
Business	7,221,509	.0338676	.0491659	.000999	.8564593
Climate Change	7,221,509	.0379281	.0481144	.000788	.6946565
Pandemic Relief Bill	7,221,509	.0417131	.0594962	.0006406	.776
Covid-19 - Safety Measures	7,221,509	.0380996	.0495135	.0006406	.6703297
Sport	7,221,509	.0413853	.066688	.0006406	.7362637
Space Travel	7,221,509	.0372777	.0506855	.0009662	.6732864
Entertainment	7,221,509	.042795	.0659412	.000993	.7514124
Weather	7,221,509	.0378354	.0561839	.0006406	.8566308
The Legal System	7,221,509	.0409268	.0598626	.0006406	.7113402
Urban Centres	7,221,509	.0327092	.0414814	.0009662	.9362101
Education System	7,221,509	.0388167	.0539481	.000788	.7342657
Family Life	7,221,509	.039968	.0534075	.0006406	.6712329
Covid-19 - Case Numbers & Death Toll	7,221,509	.0422263	.0664649	.0006406	.803681
Protests	7,221,509	.0448087	.0712441	.0006406	.7362637
2020 Elections (All)	7,221,509	.0417701	.0620603	.000788	.7639752
International Relations	7,221,509	.0397616	.0592671	.0006406	.8074866
Site Self Reference/Promotion	7,221,509	.0381786	.04915	.0006406	.6831683
Covid-19 - Vaccines	7,221,509	.0413877	.0583525	.0006406	.7664234
Traffic	7,221,509	.0399376	.0594774	.0006406	.7313433
Race Relations	7,221,509	.0410059	.0554961	.0006406	.7106918
Shopping	7,221,509	.039472	.0569222	.0006406	.8153846
Covid 19 - State Stay at Home Orders	7,221,509	.0401633	.0549633	.0006406	.7324841

Table B.2: News Articles/Headlines Dataset Summary Statistics

Variable	N	Mean	St.Dev	Minimum	Maximum
Fear	180,715	1.612243	1.781524	0	100
Anger	180,715	1.287503	1.544174	0	10
Ideological Bias	180,715	1.877068	.9922472	0	3
Standard of Reporting	180,715	3.011622	.6762937	0	4
2020 Election - General	180,715	.050876	.1126614	.0000641	.9304551
Social Media	180,715	.0369214	.0765551	.0000933	.8874074
Covid-19: China	180,715	.0322715	.0790344	.0001075	.8156028
Education System	180,715	..0295109	.0603571	.0001032	.7795591
Protests	180,715	.0464973	.1080029	.0001002	.9306804
Covid-19: Europe	180,715	.0324701	.0791841	.0000857	.9026426
The Legal System	180,715	.0338861	.0782002	.0000641	.8362168
Race Relations	180,715	..032402	.0661097	.0001084	.7924264
Climate Change	180,715	.0372029	.0879891	.0001013	.9333968
Immigration	180,715	.0274603	.0693954	.0001044	.9004815
Sport	180,715	.0420128	.1142531	.0000906	.9704978
The Education System	180,715	.0367575	.1075949	.0000569	.9232506
Business	180,715	.0569004	.1301293	.0000859	.8992806
Iran	180,715	.0337976	.0936709	.0000641	.9222857
Covid-19: General	180,715	.0521189	.1094338	.0000981	.8651994
Entertainment	180,715	.0472109	.1054396	.0000641	.878453
USA	180,715	.0418381	.0728636	.0001121	.8291551
Covid 19: Relief Measures	180,715	.0419282	.0818283	.0000641	.8735441
Covid 19: Cities	180,715	.0505784	.0942221	.0000857	.8666667
Impeachment	180,715	.0522458	.0875213	.0000641	.7914692
Trump Allies Investigations	180,715	.0375711	.0843545	.0001002	.9084406
2020 Presidential Elections	180,715	.0292459	.0654139	.0000981	.7979044
News	180,715	.0356896	.0596451	.0000981	.7831325

B.2 Overview of LDA Topics

B.2.1 Facebook Dataset

Table B.3: Overview of LDA Topics

Topic Number	Topic Label	Tokens
Topic 1	2020 Presidential Election	“trump”, “presid”, “biden”, “joe”, “hous”, “donald”, “white”, “say”, “campaign”, “call”, “impeach”, “support”, “administr”, “former”, “obama”
Topic 2	Business	“busi”, “accord”, “read”, “compani”, “industri”, “employe”, “million”, “market”, “week”, “percent”, “near”, “counti”, “sale”, “price”, “billion”
Topic 3	Climate Change	“can”, “change”, “help”, “climat”, “way”, “studi”, “research”, “may”, “use”, “green”, “new”, “work”, “system”, “problem”, “scienc”,
Topic 4	Pandemic Relief Bill	“million”, “job”, “bill”, “fund”, “pay”, “money”, “help”, “pandem”, “tax”, “worker”, “cut”, “relief”, “american”, “econom”, “feder”,
Topic 5	Covid-19 Safety Measures	“mask”, “social”, “post”, “face”, “media”, “use”, “video”, “wear”, “call”, “new”, “twitter”, “facebook”, “distanc”, “say”, “app”,

B.2.2 Article/Headline Dataset

Table B.3: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 6	Sport	“game”, “team”, “season”, “sport”, “play”, “football”, “winner”, “player”, “coach”, “big”, “basketball”, “first”, “nfl”, “super”, “fan”,
Topic 7	Space Travel	“look”, “photo”, “space”, “world”, “travel”, “moon”, “light”, “art”, “around”, “orbit”, “around”, “launch”, “ship”, “take”, “star”,
Topic 8	Junk	“year”, “day”, “first”, “time”, “last”, “week”, “month”, “one”, “histori”, “back”, “since”, “look”, “two”, “happen”, “next”,
Topic 9	Entertainment	“star”, “show”, “movi”, “celebr”, “film”, “birthday”, “music”, “king”, “die”, “perform”, “new”, “best”, “seri”, “john”, “actor”,
Topic 10	Weather	“north”, “west”, “south”, “storm”, “carolina”, “area”, “weather”, “expect”, “central”, “beach”, “weekend”, “morn”, “across”, “florida”, “island”,

Table B.3: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 11	Junk	"know", "go", "like", "get", "want", "thing", "just", "need", "can", "make", "people", "think", "us", "one", "say"
Topic 12	Legal System	"court", "law", "feder", "judg", "rule", "suprem", "prison", "justic", "attorney", "alleg", "file", "investig", "lawsuit", "legal", "general"
Topic 13	Urban Centres	"citi", "new", "york", "mayor", "san", "st", "de", "council", "town", "angel", "open", "center", "resid", "build", "los"
Topic 14	Education System	"school", "student", "high", "univers", "plan", "colleg", "learn", "public", "cancel", "educ", "district", "board", "virtual", "class", "meet"
Topic 15	Family Life	"famili", "home", "children", "life", "love", "die", "dog", "babi", "help", "kid", "girl", "friend", "one", "son", "mother"

Table B.3: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 16	Covid-19 Case Numbers and Death Toll	"case", "new", "coronavirus", "count", "report", "test", "death", 'posit'", "state", "number", "offic", "confirm", "health", "updat", "record"
Topic 17	Protests	"polic", "man", "offic", "protest", "arrest", "charg", "shoot", "kill", "say", "shot", "woman", "gun", "georg", "suspect", "death"
Topic 18	2020 Election (All)	"elect", "vote", "democrat", "senat", "state", "reoublican", "voter", "parti", "ballot", "race", "candid", "poll", "presidenti", "georgia", "win"
Topic 19	International Relations	"china", "us", "forc", "nation", "countri", "war", "militari", "govern", "secur", "world", "said", "unit", "iran", "chines", "veteran"
Topic 20	Site Self Reference/Promotion	"news", "live", "photo", "watch", "today", "story", "join", "us", "update", "daili", "noq", "show", "question", "latest", "discuss"

Table B.3: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 21	Covid-19 Vaccines	“coronavirus”, “health”, “vaccin”, “vaccin”, “scien”, “research”, “virus”, “pfzer”, “medic”, “dr”, “expert”, “lab”, “patient”, “trump”, “warp”
Topic 22	Traffic	“fire”, “crash”, “car”, “near”, “kill”, “dead”, “road”, “driver”, “found”, “two”, “home”, “die”, “people”, “drive”, “vehicle”
Topic 23	Race Relations	“’black’, “american”, “right”, “peopl”, “qomen”, “live”, “america”, “matter”, “church”, “communiti”, “white”, “nation”, “protest”, “floyd”, “violen”
Topic 24	Shopping	“food”, “make”, “can”, “store”, “get”, “best”, “holiday”, “home”, “shop”, “free”, “hand”, “help”, “offer”, “christmas”, “deal”
Topic 25	Covid 19 Stay at Home Orders	“state”, “order”, “coronavirus”, “close”, “reopen”, “gov”, “governor”, “new”, “open”, “plan”, “pandem”, “announc”, “travel”, “restrict”, “california”

Table B.4: Overview of LDA Topics

Topic Number	Topic Label	Tokens
Topic 1	2020 Election - General	"electio', "vote", "democrat", "state", "trump", "voter" "campaign", "biden", "presid" "ballot", "poll", "republican" "candid", "congress", "senat"
Topic 2	Social Media	"news", "twitter", "report", "media", "compani", "facebook", "post", "daiil", "content", "tech", "instagram", "caller", "tweet", 'social'" "video"
Topic 3	Covid-19: China	"china", "cines", "coronavirus", "report", "countri", "world", "govern", "nation", "wuhan", "state", "virus", "communist", "offici", "hong", "kong"
Topic 4	Education System	"school", "student", "univers", "children", "women", "famil", "educ", "year", "child", "high", "parent", "college", "report", "accord", "sexual'
Topic 5	Protests	"polic", "offic", "protest", "report", "citi", "black", "arrest", "man", "death", "floyd", "fire", "accord", "charg", "video", "depart",

Table B.4: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 6	News	“fox”, “cnn”, “news”, “subscrib”, “report”, “video”, “click”, “top”, “flash”, “break”, “confer”, “headlin”, “time”, “report”, “newspaper”
Topic 7	Covid-19: Europe	“london”, “covid”, “europ”, “’govern’, “minist”, “european”, “italy”, “world”, “countri”, “johnson”, “british”, “uk”, “britain”, “reuter”, “eu”
Topic 8	The Legal System	“court”, “law”, “suprem”, “state”, “justic”, “rule”, “judge”, “right”, “senat”, “barrett”, “constitut”, “case”, “legal”, “abort”, “amend”
Topic 9	Race Relations	“black”, “peopl”, “live”, “church”, “white”, “matter”, “nation”, “communiti”, “american”, “support”, “protest”, “america”, “group”, “christian”, “right”,
Topic 10	Climate Change	“can”, “food”, “space”, “storm”, “flood”, “year”, “time”, “fire”, “pollut”, “green”, “new”, “temperat”, “heat”, “weather”, “winter”,

Table B.4: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 11	Immigration	“border”, “immigr”, “illeg”, “migrant”, “report”, “flight”, “mexico”, “travel”, “texa”, “airlin”, “trump”, “offici”, “state’, “ship”, “passeng”
Topic 12	News	“still”, “site”, “share”, “content”, “inform”, “read”, “storm”, “fact”, “reader” “us”, “sourc”, “discern”, “mind”, “opinion”, “articl”,
Topic 13	Sport	“’game’, “team”, “season”, “play”, “player”, “sport”, “first”, “leagu”, “nfl” “two”, “win”, “nba”, “year”, “last”, “second”,
Topic 14	Junk	“go”, “peopl”, “think”, “know”, “get”, “just”, “see”, “say”, “like” “want”, “said”, “now”, “thing”, “can”, “right”,
Topic 15	The Education System	“universit”, “college”, “degree”, “undergrad”, “iveagh”, “professor”, “scholarship”, ‘sport”, “cancel” “coed”, “young”, “school”, “’grade’, “graduat”, “postgrad”,

Table B.4: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 16	Business	“compani”, “year”, “market”, “bank”, “reuter”, “billion”, “price”, “million”, “busi” “new”, “month”, “market”, “economi”, “rate”, “product”
Topic 17	Iran	“iran”, “militari”, “attack”, “test”, “state”, “israel”, “forc”, “kill”, “war”, “’secur’, “nation”, “iranian”, “countri”, “unit”, “presid”,
Topic 18	Covid-19: General	“coronavirus”, “health”, “test”, “virus”, “vaccin”, “case”, “hospit”, “announc”, “medic”, “death”, “patient”, “infect”, “disease”, “people”, “dr”,
Topic 19	Entertainment	“star”, “show”, “entertain”, “love”, “film”, “famil”, “year”, “photo”, “time”, “’share’, “celebr”, “ima”, “movi”, “tv”, “stream”,
Topic 20	USA	“one”, “even”, “time”, “advertis”, “like”, “usa”, “american” “america”, “polit” “world”, “power”, “super”, “global”, “year”, “nuclear’

Table B.4: Overview of LDA Topics (continued)

Topic Number	Topic Label	Tokens
Topic 21	Covid 19: Relief Measures	“coronavirus”, “american”, “worker”, “million”, “fund”, “bill”, “job”, “busi”, “work”, “govern”, “money”, “relief”, “’program’, “feder”, “plan”,
Topic 22	Covid 19: Cities	“coronavirus”, “new”, “state”, “la”, “ypul”, “citi”, “peopl”, “mask”, “home” “order”, “pandem”, “mayor”, “governor”, “health”, “close”,
Topic 23	Impeachment	“trump”, “hous”, “donald”, “senat”, “white”, “democrat”, “pence”, “republican”, “polit”, “pelosi”, “impeach”, “charge”, “american”, “call”, “news”,
Topic 24	Trump Allies Investigations	“invetig”, “report”, “alleg”, “said”, “former”, “attorney”, “fbi”, “depart”, “case”, “general”, “charg”, “offici”, “intellig”, “flynn”, “inform”,
Topic 25	2020 Presidential Elections	“’biden’, “joe”, “persid”, “vice”, “former”, “trump”, “debat‘”, “campaign”, “presidenti”, “class”, “hunter”, “fraud”, “quot”, “harris”, “pence”,

B.3 Full Ordinary Least Squares Regression Results

Table B.5: Facebook Posts Full Regression Results

	Fear	**Anger**
Conspiratorial Sites	0.377	0.067
	(0.000)	(0.000)
Ideological Bias	0.003	−0.020
	(0.931)	(0.466)
Standard of Reporting	−0.213	−0.289
	(0.000)	(0.000)
2020 Presidential Election	1.736	2.880
	(0.000)	(0.000)
Business	−8.311	−4.610
	(0.000)	(0.000)
Climate Change	5.595	−1.640
	(0.000)	(0.000)
Pandemic Relief Bill	−9.319	0.996
	(0.000)	(0.000)
Covid-19 Safety Measures	1.452	2.480
	(0.000)	(0.000)
Sport	−0.592	1.321
	(0.000)	(0.000)
Space Travel	6.620	−0.439
	(0.000)	(0.000)
Entertainment	−0.913	−3.033
	(0.000)	(0.000)
Weather	4.672	11.607
	(0.000)	(0.000)
The Legal System	27.343	26.122
	(0.000)	(0.000)
Urban Centres	−3.326	−1.495
	(0.000)	(0.000)
Education System	−12.965	−7.623
	(0.000)	(0.000)
Family Life	2.170	−3.681
	(0.000)	(0.000)
Covid-19 Case Numbers abd Death Toll	28.482	1.744
	(0.000)	(0.000)
Protests	35.087	29.248
	(0.000)	(0.000)
2020 Election (All)	−7.333	5.385
	(0.000)	(0.000)
International Relations	13.519	9.046
	(0.000)	(0.000)
Site Self Reference/Promotion	6.121	−7.704
	(0.000)	(0.000)
Covid-19 Vaccines	9.015	−0.131
	(0.000)	(0.552)
Traffic	33.705	4.248
	(0.000)	(0.000)
Race Relations	0.687	3.667
	0.013	0.000
Shopping	−7.380	−2.422
	(0.000)	(0.000)
Covid 19: Stay at Home Orders	2.342	−3.511
	(0.000)	(0.000)

Note: p-values in parentheses

Table B.6: News Articles Full Regression Results

	Fear	**Anger**
Conspiratorial Sites	−0.083	0.0004
	(0.517)	(0.997)
Ideological Bias	0.054	0.016
	(0.538)	(0.815)
Standard of Reporting	−0.058	−0.013
	(0.552)	(0.854)
Period	0.188	0.017
	(0.000)	(0.418)
2020 Election - General	−0.396	1.365
	(0.132)	(0.000)
Social Media	0.243	0.100
	(0.401)	(0.728)
Covid-19 China	0.824	0.358
	(0.019)	(0.158)
Education System	0.122	−0.038
	(0.784)	(0.861)
News	5.140	4.064
	(0.000)	(0.000)
Covid-19: Europe	0.571	0.329
	(0.118)	(0.200)
The Legal System	4.617	4.028
	(0.000)	(0.000)
Race Relations	1.257	1.084
	(0.000)	(0.000)
Climate Change	0.285	0.015
	(0.426)	(0.965)
Immigration	1.738	0.597
	(0.000)	(0.006)
Sport	−0.065	0.087
	(0.845)	(0.760)
The Education System	0.537	0.661
	(0.126)	(0.027)
Business	−0.299	0.091
	(0.305)	(0.718)
Iran	3.003	2.286
	(0.000)	(0.000)
Covid-19: General	1.744	0.412
	(0.000)	(0.235)
Entertainment	0.103	0.106
	(0.717)	(0.662)
USA	1.039	0.657
	(0.003)	(0.014)
Covid-19: Relief Measures	−0.863	−0.014
	(0.000)	(0.957)
Covid-19: Cities	0.376	−0.455
	(0.241)	(0.055)
Impeachment	0.856	0.630
	(0.237)	(0.204)
Trump Allies Investigations	3.278	2.886
	(0.000)	(0.000)
2020 Presidential Election	0.055	−0.348
	(0.906)	(0.480)

Note: p-values in parentheses

Table B.7: News Headlines Full Regression Results

	Fear	**Anger**
Conspiratorial Sites	0.661	0.631
	(0.019)	(0.002)
Ideological Bias	−0.225	−0.284
	(0.202)	(0.031)
Standard of Reporting	0.196	0.185
	(0.299)	(0.071)
Period	0.159	−0.043
	(0.320)	(0.771)
2020 Election - General	−0.431	2.439
	(0.534)	(0.002)
Social Media	1.527	1.417
	(0.231)	(0.207)
Covid-19 China	2.132	1.463
	(0.023)	(0.109)
Education System	1.974	0.765
	(0.005)	(0.450)
News	14.045	9.847
	(0.000)	(0.000)
Covid-19: Europe	2.615	1.695
	(0.033)	(0.144)
The Legal System	10.046	9.215
	(0.000)	(0.000)
Race Relations	0.530	0.876
	(0.638)	(0.289)
Climate Change	1.763	0.302
	(0.021)	(0.549)
Immigration	5.635	2.546
	(0.000)	(0.062)
Sport	0.253	0.127
	(0.781)	(0.844)
The Education System	0.907	0.385
	(0.308)	(0.581)
Business	0.418	0.740
	(0.626)	(0.262)
Iran	6.410	5.016
	(0.000)	(0.000)
Covid-19: General	3.839	1.097
	(0.000)	(0.099)
Entertainment	0.663	0.186
	(0.489)	(0.804)
USA	1.079	0.043
	(0.243)	(0.967)
Covid-19: Relief Measures	−1.566	−0.125
	(0.110)	(0.832)
Covid-19: Cities	1.246	−0.062
	(0.056)	(0.922)
Impeachment	1.209	0.162
	(0.065)	(0.774)
Trump Allies Investigations	7.123	5.594
	(0.000)	(0.000)
2020 Presidential Election	1.209	−0.726
	(0.226)	(0.156)

Note: p-values in parentheses

Appendix C

Chapter 5 Appendices

C.1 Full Ordinary Least Squares Regression Results

Table C.1: Over Performance Score Full Regression Results

	(1)	(2)	(3)
Fear	0.037	0.042	0.063
	(0.000)	(0.000)	(0.000)
Anger	0.018	0.017	0.022
	(0.000)	(0.001)	(0.000)
Fear/Conspiracy Interaction		0.055	
		(0.000)	
Anger/Conspiracy Interaction		0.020	
		(0.000)	
Conspiratorial News Outlets	1.476	1.906	
	(0.272)	(0.172)	
Ideological Bias	−0.724	−0.720	−0.203
	(0.000)	(0.000)	(0.208)
Standard of Reporting	−0.971	−0.971	0.128
	(0.024)	(0.024)	(0.764)
Page Likes	0.000	0.000	−0.000
	(0.029)	(0.028)	(0.061)
Link	0.991	0.964	0.292
	(0.633)	(0.645)	(0.736)
Live Video (Complete)	8.213	8.171	0.985
	(0.000)	(0.000)	(0.434)
Live Video (Scheduled)	−10.106	−10.144	−5.718
	(0.010)	(0.010)	(0.118)
Native Video	6.819	6.796	0.913
	(0.001)	(0.001)	(0.537)
Photo	3.827	3.794	−1.272
	(0.069)	(0.073)	(0.319)
Status	1.972	1.936	−0.750
	(0.393)	(0.404)	(0.575)
Video	3.378	3.350	0.362
	(0.089)	(0.094)	(0.848)
YouTube	2.808	2.825	−1.327
	(0.269)	(0.265)	(0.390)
Presidential Election1	46.666	46.658	12.239
	(0.000)	(0.000)	(0.000)
Business	−4.320	−4.295	−8.330
	(0.118)	(0.120)	(0.092)
Climate Change	5.567	5.570	−8.031
	(0.014)	(0.014)	(0.001)
Pandemic Relief Bill	14.619	14.641	3.272
	(0.000)	(0.000)	(0.219)
Covid-19 Safety Measures	16.682	16.687	−3.304
	(0.000)	(0.000)	(0.134)
Sport	−27.819	−27.801	−5.014
	(0.000)	(0.000)	(0.173)
Space Travel	11.719	11.725	1.096
	(0.002)	(0.002)	(0.657)
Entertainment	−3.633	−3.632	−8.524
	(0.307)	(0.306)	(0.002)
Weather	4.756	4.759	−6.108
	(0.232)	(0.232)	(0.117)
The Legal System	18.899	18.906	4.996
	(0.000)	(0.000)	(0.010)
Urban Centres	12.782	12.803	3.184
	(0.000)	(0.000)	(0.31)4
Education System	4.738	4.783	−5.931
	(0.077)	(0.075)	(0.080)
Family Life	25.726	25.701	1.469
	(0.000)	(0.000)	(0.677)
Covid-19 Case Numbers and Death Toll	19.695	19.589	−1.662
	(0.000)	(0.000)	(0.579)
Protests	29.003	28.971	10.297
	(0.000)	(0.000)	(0.000)
2020 Elections (All)	21.983	21.976	5.830
	(0.000)	(0.000)	(0.005)
International Relations	20.966	20.958	−3.275
	(0.000)	(0.000)	(0.277)
Site Self Reference/Promotion	−35.232	−35.242	−14.176
	(0.000)	(0.000)	(0.007)
Covid-19 - Vaccines	24.851	24.846	−1.055
	(0.000)	(0.000)	(0.634)
Traffic	22.921	22.807	4.316
	(0.000)	(0.000)	(0.023)
Race Relations	29.308	29.295	6.863
	(0.000)	(0.000)	(0.158)
Shopping	−6.356	−6.345	−7.946
	(0.000)	(0.000)	(0.026)
Covid-19 State Stay at Home Orders	31.338	31.334	3.739
	(0.000)	(0.000)	(0.074)

p-values in parentheses

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