Us v.s. Them in 280 Characters: Why Political Polarization Fuels Vicious Attacks on Twitter

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Abstract

Strategies of negative campaigning were put in heavy use in the 2016 presidential campaigns. Candidates from both major political parties attacked their opponents by spreading scandals, name-calling, and attacking on their characters. Such attempts to decrease the likability of their opponents among voters are amplified by mass media, specifically, television, newspaper, and the Internet. But why are the election campaigns so negative? The study of psychology offers us an intuitive explanation. When humans are placed into groups, whether they are divided along with the stance on the important issues of politics, or with the most mundane matter such as teams in a tug-of-war game, it is natural to develop distaste for the opponent. This study draws a causal relationship between the division along the partisan lines and the level of vicious negative political campaigns. Specifically, I examine 29,062 tweets

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that were tweeted by the gubernatorial candidates within the last three months leading up to the 2014 gubernatorial race across 36 states. I also measure two levels of polarization: 1) party elite polarization, the division in the legislature along party lines, and 2) mass polarization, the divergence of opinions on key political issues within the electorate. In turn, I propose two models that suggest polarization drives vicious attacks. One model models the top-down pressure — the greater the division among party elites in a state the more likely the candidates will use negative campaigning strategies against their opponents. In parallel, the other model models the bottom-up pressure, which establishes the same causal mechanism but instead pressures on the candidates come from the electorate. To quantify negative campaigns on Twitter, I measure the candidates' tweets' viciousness scored on a novel index called the Political Tweet Viciousness Index (PTVI). I found that the top-down model is a better model at explaining the relationship between polarization and vicious attacks.

1 Introduction

Recalling the 2016 presidential election, a chilling stream of scandals, name calling, and vicious attacks would surface to any American's mind. The heat of the contention can be illustrated when Donald Trump tweeted "Obama just endorsed Crooked Hillary. He wants four more years of Obama — but nobody else does!", and Hillary Clinton replied "Delete your account." which soon became one of her most popular tweets. This forms a sharp contrast to a supposedly civil and temperate policy debate. After all, how is calling a fellow politician "Crooked" making America great and how is asking your opponent to delete their Twitter account making us stronger together?

James Madison argued in *Federalist No. 10* for a rather chilling cause: "[t]he latent causes of faction are thus sown in the nature of man... [a] zeal for different opinions concerning religion, concerning government, and many other points, ... divided mankind into parties, inflamed them with mutual animosity, and rendered them much more disposed to vex and oppress each other than to co-operate for their common good" (Madison (1787)). Is Madison right that factions lead to "mutual animosity"? Recently scholars have also attributed the increasing degree of political attacks in political campaigns to party polarization (Sinclair (2003); Layman, Carsey and Horowitz (2006)). Sinclair (2003) observed that these campaigns are being perceived as less civil by "the growing degree to which political advertising attacking opponents". Layman, Carsey and Horowitz (2006) also note that party polarization is accompanied by "a nasty, ad hominem politics, ... [and] the politics of personal destruction". Indeed, an observer of the 2016 presidential campaign would note a large number of negative and vicious attacks coming from both major parties in the general election. At the same time, Jacobson (2016) demonstrates the level of polarization among elites by showing how partisans simply refuse to compromise — even some of the most anti-Trump Republicans would refuse to vote for Clinton if faced with Trump-Clinton general election race. These qualitative observations suggest the rising level of polarization coincide with the increasing use of negative campaigning.

At the same time, more and more politicians have incorporated social media platforms into their election campaigns, giving researchers a unique opportunity to study negative campaigning and its relationship with polarization. Perhaps most prominently, politicians use Twitter as a way to strengthen their election campaigns by directly interacting with the voters, sharing campaign information, mobilizing their base, and so on. They are assumed to carefully strategize the content of their tweets and what they retweet to engage their audience (Evans, Cordova and Sipole (2014); Ii, García-Carretero and Broersma (2019)). One of the ways candidates use traditional media platforms to engage their audience is by running attack ads, which evolved into attack tweets in the age of Twitter. Evans, Cordova and Sipole (2014) observed that 10% of tweets from 2012 House candidates are attack tweets during their election campaigns. Lee and Xu (2018) suggested that 50% of all tweets from 2016 presidential contestants, Hillary Clinton and Donald Trump, were attack tweets in the last three months leading up to the election. The availability of these Twitter content and metadata allows for a systematic analysis of negative campaigning.

This paper investigates the effect of political polarization on the tendency of a candidate to go negative on Twitter. It asks, *to what extent does political polarization, both party polarization and mass polarization, lead to a larger number of and more vicious attacks on Twitter*? Specifically, I will examine the effect of the levels of polarization in different states on the quantity and viciousness of attack tweets from the political candidates in the gubernatorial elections of 2014. This is a timely topic in the age of internet and the emergence of more partisan conflicts in the U.S. With candidates adopting Twitter, and potentially reaching more and more young people than traditional media can, this level of negativity could set an unproductive and perhaps dangerous norm of politics for the next generation of Americans. This study provides an explanation of why negative messages sometimes dominate election campaigns. It paints a picture of how partisanship shapes the landscape of American public discourse.

In the following sections, I will first introduce prior studies on political polarization, its different manifestations in American politics and its effects. Then, I will proceed to discuss how negativity has been used as a campaign tool in the age of television and how this translates today on the internet. A theoretical discussion will then unfold where I will link political polarization to campaign negativity on Twitter through two parallel models — one is bottom-up where the candidates are influence by the voters, and the other is top-down where the candidates are influenced by the political elites. I will then formally introduce the hypotheses. In the Data Section, I will show how to measure polarization and negativity, and several control variables. In the Methods Section, I will introduce a novel index for measuring the viciousness of a campaign tweet, and show the multivariate regression model used for the analysis. It is then followed by the results of my analysis and a further discussion its implications on the elections and American politics.

2 Political Polarization

2.1 Definition

Political polarization refers to the phenomenon of a widening gap between the policy positions taken by the two major American parties (Layman, Carsey and Horowitz (2006)). Along with this gap is the American public associating with themselves with one of the political parties. The polarization takes place on two levels: one among the elites and one among the populace, which is frequently referred to as "party polarization" and "popular polarization" (or "mass polarization"), respectively. With the Democrats moving further to the left and the Republicans to the right, pundits, journalists, and empirical researchers observe that the level of polarization has been increasing over the years (Layman, Carsey and Horowitz (2006)).

As political scientists pay more attention to polarization, there is a growing interest in finding out what are the consequences and implications of such division in ideology and partisan identity. Is the plurality of ideas good for democracy? Or does it simply exacerbate the problems of gridlock in the government? In this study, I focus on polarization's effects on elections and, specifically, its impact on the civility of candidates' discourse in a gubernatorial race.

2.2 Group, Affective, and Moral Polarization

Mason (2018) argues that group identity is the key underlying mechanism to political polarization by showing a 1954 psychology experiment in Robbers Cave State Park. In the experiment, two groups of very similar boys were divided into two groups, who named themselves the Eagles and the Rattlers. They were kept separate for a week for bonding and team building. When they first learned each other's existence in the second week, they referred to each other as "outsiders" and "intruders" (Mason (2018)). When they were first pit against each other in a competitive game, they began name-calling members on opposing teams with derogatory names. Soon, the conflicts grew into flag burning, fist fighting, and raiding the other team's cabins. This experiment concluded that it is really easy to turn originally similar people into "two nearly warring tribes, with only the gentle nudge of isolation and competition to encourage them" (Mason (2018)). Mason reflects the implication of this experiment on our current political environment. She attributes an environment of tribal conflicts between the Democratic and Republican Party bases today to Donald Trump's strong partisan rhetoric which provided that nudge of competition and us-vs-them mentality.

Scholars capture the phenomenon where self-identifying partisans grow an increasingly intense distaste for those on the other side of the ideological spectrum in a term called "affective polarization" or "moral polarization". Affective polarization is defined around the sense of belonging to a group and the partisan identity rather than disagreements in politics. It demonstrates a pure hostility against the out-group identity even when there is no significant difference in preferences of policy. In America, this effect is observed by scholars like Tappin and McKay (2019): "[while] the average American is not particularly committed to one ideological viewpoint over another, they do appear committed to a partisan group identity; that is, for the average American voter, politics may be more a case of Us vs. Them, than 'our policy' vs. 'their policy' (Kinder and Kalmoe (2017))." What makes it dangerous is that affective polarization divides the country like the Eagles and the Rattlers in the Robbers Cave Experiment — conflicts are created on which side of the aisle one happens to be on. Political discussions easily deteriorate from a civil, purposeful debate on how to govern to a spiteful, merit-less verbal fray degrading the character of one's political opponent.

2.3 Current Level of Political Polarization

The current level of political polarization is higher than that in the past few decades. A survey study in 2014 found that "[the] overall share of Americans who express consistently conservative or consistently liberal opinions has doubled over the past two decades from 10% to 21%" (*2014 Political Polarization Survey* (2014)). Not only are people holding more consistent ideologies, but they also found growing mutual dislike between the parties. In 2014, 38% of the Democrats view the Republican

Party as "very unfavorable" while 43% of the Republicans viewed the Democratic party the same way. This had more than doubled what it was like in 1994. More detrimentally, 27% of the Democrats view the other side "a threat to the national well-being" and 36% of the Republicans shared the sentiment against the Democrats (*2014 Political Polarization Survey* (2014)).

Increasing polarization does not only exist among the masses but among political elites as well. According to Jensen (2017), in 1981, more than one-third of the House Democrats and more than one half of the House Republicans were considered moderates. However, by 2009, there was only one-quarter of the House Democrats and one-percent of the House Republicans who were considered moderates (Jensen (2017)). The decline of the elites in the ideological middle means they are taking more and more extreme positions on issues, which is a strong indication of polarization.

2.4 Political Polarization at the State Level

Party polarization does not only happen in Congress, it also exists at the state level. Theorists believe that the level of polarization of the state legislatures is influenced by a polarizing public, influential interest groups, and a more and more polarized national government (Grumbach (2018)). In particular, a polarizing national government causes the policy-demanders to turn to states where the policy victory is unlikely to be struck down by a gridlocked Washington. At the same time, Congress members delegate authority to states as a "second-best option" (Grumbach, 2018). This trend of state delegation is often referred by scholars as the "devolution revolution", and coincides with the rising level of polarization (Grumbach (2018)). Boris Shor and Nolan McCarty measured the level of party polarization on the state level. They did so with a spatial model of state legislature roll call data mapped into National Political Awareness Test (NPAT) common space (Shor and McCarty (2011)). Empirically, they showed that ideological mean between the Democratic and Republican Party has been polarized in several states for at least the 2000s and the late 1990s. Different states have different levels of polarization, where California is "by far the most polarized state legislature" while "Rhode Island and Louisiana are the least polarized" (Shor and McCarty (2011)). In addition to varying degree of polarization, they also found that most states are becoming increasing polarized while only a few are becoming increasing depolarized (Shor and McCarty (2011)).

This study draws on the variation in state polarization in order to examine the relationship between negative campaigning and polarization with respect to states rather than time. This is helpful because it enables us to study the subject comparatively. Because Twitter is relatively new platform (founded in 2006) and has only recently been adopted by politicians, I cannot compare multiple elections across a long period of time. However, since there is enough variation in different states, it allows me to focus on geographical variations rather than temporal variations.

3 Negativity and Attack Ads

3.1 What is Negativity in A Campaign?

There are many ways researchers and politicians define negativity. Based on past literature on campaigns ads, negativity exists where a candidate uses negative appeal in their ad content (Geer (2006)). For example, a candidate can frame the same issue such that it focuses on the gain of electing them (positive appeal) or the cost of not electing them (negative appeal). Under this broad definition of negativity, negative appeals may not involve explicit attacks. In contrast with this broad definition, then-Vice-President George H. W. Bush argued that a campaign ad is not negative if rhetoric "[tries] to help the American people understand the differences [of candidates' positions on issues]" (Geer (2006)). Indeed, Bush speaks to an important distinction between contrasts and attacks. A contrast explicitly highlights the value of picking the candidate and the cost of picking the opponent, whereas an attack only contains the latter. Under Bush's definition, contrasts are productive, informative, and non-negative. Lastly, Geer (2006) prefers a more direct and clear-cut definition of negativity: "negativity is any criticism leveled by one candidate against another during a campaign". Under this definition, Bush's non-negative contrast campaign ads are indeed negative.

3.2 History of Attack Ads

The long history of negative campaigning dates all the way back to the Roman Empire, where "members of the Senate used methods of negative campaigning to achieve their goals" (Spiller (2014)). Politicians would attack their opponents by putting endorsement ads on the walls and tombs pretending to be questionable supporters such as "runaway slaves, gamblers and prostitutes" (Freeman (2012)). While the method is rudimentary, these attack campaigns demonstrate the co-existence of elections and negative campaign tactics since the dawn of democracy.

In the United States, negative campaigning is also not new. One famous example of this is the "seminal" negative campaign ad, the 1964 Daisy Girl campaign that Lyndon B. Johnson used to attack Barry Goldwater (Spiller (2014)). Johnson indirectly refers to Goldwater's position on nuclear weapons as dangerous using emotional appeals. The Daisy Girl ad is a landmark negative campaign ad because it shows that negative campaigning advantages its sponsoring candidate. This relates to the media's role as the ad-watch, which created "phantom advertising" that provides the sponsor with free publicity when they leak the ad to the media (Weber (2008)). The Daisy Girl ad not only caused controversies but also received a great deal of free ad time through media attention. The ad was only aired once but all three major networks picked it up and discussed it (Weber (2008)). This highlights two key advantages of why campaigns would go negative. Firstly, TV ads have a very limited length, and "negativity is often a more effective strategy" under time constraints (Weber (2008)). In addition, media is more likely to cover a negative ad because they attract more viewers to their network (Weber (2008)). Given the large exposure from television news, it is very appealing for a lesser-known candidate or candidates in close races to go negative.

3.3 Effects of Attack Ads

Negativity, however, comes at a cost. First is at the expense of civility. Kimball (2003) remarks that: "Bush and Gore campaigns spent over $600 million on the 2000 primary, congressional, and presidential contests. Commercials are used to attack opponents personally, sometimes at the expense of truth. The result is to make elections often divisive and shrill, rather than a temperate discussion of public policy." Negative campaigning on the opponent's irrelevant character traits do not add to the discourse of public policy. In addition, negative ads can keep people away from the polls. They discourage the supporters of the candidate being attacked and "make the public disenchanted with both candidates" (Spiller (2014)). This demobilizing effect can diminish the power of civic duty and undermine the legitimacy of the electoral process (Spiller (2014)).

4 Twitter and Attack Tweets

4.1 From the Internet to Twitter

The rise of internet has slowly shifted where American voters engage in politics — it is becoming the central hub where people get political information, discuss politics, and share political news and opinions. During the 2008 presidential campaign, "[nearly] a quarter of Americans (24%) say they regularly learn something about the campaign from the internet, almost double the percentage from a comparable point in the 2004 campaign (13%)" (*The Internet Gains in Politics* (2008)). This increased usage of the internet is especially evident amongst young Americans. During the 2008 presidential election, "42% of those ages 18 to 29 say they regularly learn about the campaign from the internet, the highest percentage for any news source" where as "[in] January 2004, just 20% of young people said they routinely got campaign news from the internet" (*The Internet Gains in Politics* (2008)).

The changing landscape of how people are engaged in politics has added a complementary component to traditional means of politicians reaching out to people. The New York Times described that the 2008 Obama campaign "[bolted] together social networking applications under the banner of a movement, ... [and] created an unforeseen force to raise money, organize locally, fight smear campaigns and get out the vote that helped them topple the Clinton machine and then John McCain and the Republicans" (Carr (2008)). Scholars like Williams et al. (2010) also argue that the victory of Barack Obama in 2008 attributes to his use of Twitter (Evans, Cordova and Sipole (2014)). By the 2012 Presidential election, politician had started using the internet to strength their campaign, and "fields of online battle ... [became] sharing song playlists on Spotify, adding frosted pumpkin bread recipes to Pinterest and posting the candidates' moments at home with the children on Instagram" (Wortham (2012)). By 2016, scholars had found that "96.6% of [U.S. House] Representatives and 100% of Senators have obtained accounts on Twitter" (Cook (2017)). The adoption is not that surprising given the vast audience and direct interaction empowered by the digital platform.

However, we have yet to see quantitative evidence that social media is able to influence the outcomes of elections. Scholars studied the UK elections and found that "candidates that had a Twitter account typically had vote shares around 1-2 percentage points higher than those who did not" (Bright et al. (2019)). This suggest a marginal effect of Twitter adoption on votes a candidate receives. However, they noted that although the boosting effect is minor, it is also significant. In competitive races, every bit of difference counts.

4.2 Attacks on Twitter

Attack ads in the traditional media translate to Twitter in the form of attack tweets. As demonstrated in the 2016 Presidential campaign, Donald Trump utilized the platform to its full potential, which the New York Times described as him "unleashing and redefining [Twitter's] power as a tool of political promotion, distraction, score-settling and attack" (Barbaro (2015)). Both Donald Trump and Hillary Clinton frequently tweeted attacks on each other's character or personality. In fact, for both of them, half of their communications on this platform are characterized on attack tweets (Lee and Xu (2018)).

However, not all candidates attack equally as much – there are several important nuances that also influence the negativity in campaigns. According to both quantitative and qualitative analysis, incumbents are less likely to attack than their challengers (Evans et al. (2017); Weber (2008)). As Weber (2008) observed, one of the benefits of going negative is that it grabs people's attention, and hence increase the name recognition of the candidate. Because incumbents usually are more well-known to the electorates than the challengers, we should expect the challengers to go negative more often than the opponent. In addition to name recognition, Evans et al. (2017) also pointed out two additional reasons why challengers are more likely to use negative campaigns: 1) they have to show to the electorates that they are "tough enough" to be a leader (Lau and Pomper (2002)), and 2) they must "call for change" in order to challenge the incumbent (Trent, Friedenberg and Denton (2011)). Evans, Cordova and Sipole (2014) empirically verified that there is a significant relationship ($p \leq .01$) between incumbency and the proportion of attacks candidates Tweet in the 2012 House election. They showed that while 1.3% of the tweets from the incumbents are attacks, attack tweets take up 8.0% of challengers' tweets.

It has also been shown that competitiveness of the race positively associated with the number of negative tweets that a candidate tweets on the congressional level (Evans et al. (2017); Evans, Cordova and Sipole (2014)). Once again, Evans et al. (2017) pointed out that "[voters] are more likely to pay attention and vote on the basis of campaign rhetoric" (Kahn and Kenney (1999)) and especially negative rhetoric. In competitive races, these difference can decide the outcome the election. Therefore, there is s a compelling reason for candidates in competitive races to go negative. Evans, Cordova and Sipole (2014) found a significant relationship ($p \leq .05$) between the competitiveness of a race to its candidates using attack tweets —- 9% of the tweets in competitive races are attacks and it is only 5.4% in non-competitive races.

There are several variations on attack tweets based on party identity as well. The Democratic and the Republican candidates are similar (i.e. there is a non-significant difference) in regards of the number of attacks on Twitter, but Republicans are more likely to attack the Democratic Party and the Democratic presidential candidate than the other way around in the 2012 House race ($p \leq .10$) (Evans, Cordova and Sipole (2014)). In comparison, third party candidates are more negative than those from the major parties — they attack the Republican and Democratic Party and their presidential candidates more than any of the two major parties in the 2012

House race ($p \leq .10$) (Evans, Cordova and Sipole (2014)). The reasoning behind the third party variation follows the same name recognition argument, as the lesser known third party candidates require more name recognition from electorates to have a chance in the general election.

Gender difference in campaign negativity has been studied in both traditional media and online social media. Procter and Schenck-Hamlin (1996) previously believed the female gender role (i.e. "cultural expectations of women as deferential, soft, and nurturing") influences them to be less vicious attackers (Evans et al. (2017)). However, some work suggest that in traditional media females are more likely to attack their opponent than man, and they have become more likely to go negative since the 1990s (Lau and Pomper (2001); Lau and Pomper (2004); Proctor, Schenck-Hamlin and Haase (1994); Bystrom (2009); Evans et al. (2017)). On Twitter, Evans, Cordova and Sipole (2014) found a significant relationship ($p \leq .10$) between gender and the number of attack tweets — female candidates tend to use 6.5% of their tweet to attack their opponent while male candidates only dedicate 4.4

5 Theory and Hypotheses

The pattern of increased attacks and polarization coincide with each other. Weber (2008) observed that "negative advertising has dramatically increased over the past 50 years, with both parties more likely to use this strategy". Sinclair (2003) and Layman, Carsey and Horowitz (2006) point out that political discussions have become increasing "strident" and "partisan" on the TV, radio and the internet, and that they feature more and more attacks. While there are many factors that could contribute to the prevalence of negativity, we cannot ignore the fact that at the same time, the level of polarization has also been increasing, and there could exist a causal relationship between the two phenomena.

Here, I propose an intuitive explanation to the causal mechanism behind polarization leading to the increasing negativity in political campaigns. Increased polarization naturally puts American politicians and its population into two camps, divided along the party line. The us-vs-them mentality transforms the forum of civil policy discussion into a pit of mutual distaste. What creates the tribal us-vs-them mentality is not what policy positions each party has taken, but rather that there is a difference at all. Just like the two teams in the Robbers Caves experiment, the election outcomes have become a matter of winning and losing rather than what policy has more merit and is preferred by the public. Such an environment breeds vicious attacks against the out-group. We should expect this to be especially evident in the heat of a political election, where candidates try to find flaws in their opponents' characters, policies, and values in order to appeal to the voters. Therefore, we should expect a greater degree of negativity in campaigns caused by a greater degree of polarization.

To be more specific, I propose two sets of parallel models. Generally, the candidates' interest is to be elected, and the electorates' interest is to elect a person with a great platform. These interests align when candidates describe and pitch their plan to the electorates, because the electorates can make an informed choice and the candidates with the most popular ideas get elected. However, these interests may not align at all times. Candidates, especially those who are challengers or in competitive races, would capitalize from a greater amount of exposure and name-recognition, which is one of benefits associated with going negative in traditionally attack ad studies Weber (2008). However, sometimes when they attack their opponents, especially using ad hominem attacks, the message does not contain the policy information needed by the electorates. In this case, the interest of the candidate is achieved but not that of the electorates. Therefore, the candidates must balance their interest and the electorates' interest and ask themselves: how much attack can I get away with? My first causal mechanism proposes a bottom-up answer to the question. If the electorates polarize over issues, there is naturally an in-group and out-group for both liberals and conservatives. Attacks against the out-group plays into the in-group identity, as "[z]ero-sum conflict between groups is easily exacerbated" (Mason (2018)). Hence the electorates under a heavy polarized configuration can tolerate more attacks against the out-group than electorates under a lower one. Therefore, the candidates can play a polarized electorate to their advantage and use more vicious attacks against their opponent. The second causal mechanism proposes a top-down solution. If there is already a polarized state legislature, then it is more likely the candidates for governor will adopt the group identity as well. This dynamic creates a political culture that is acceptable to attack the out-group which also drives up campaign negativity.

To recap, my research question is *to what extent does political polarization, both party polarization and mass polarization, lead to a larger number of and more vicious attacks on Twitter.* I test for 4 variants of a hypothesis to answer the research question. Each of the hypotheses can be falsified by showing there is no statistically significant relationship between the two variables.

H1a: There is a positive relationship between the level of the state's party polarization and the quantity of attack tweets from 2014 gubernatorial candidates.

H1b: There is a positive relationship between the level of the state's mass polarization and the quantity of attack tweets from 2014 gubernatorial candidates.

H2a: There is a positive relationship between the level of the state's party polarization and the viciousness of attack tweets from 2014 gubernatorial candidates.

H2b: There is a positive relationship between the level of the state's mass polarization and the viciousness of attack tweets from 2014 gubernatorial candidates.

One of the concerns one may raise is that state demographics can link polarization and campaign negativity, which creates a spurious correlation between the latter two. For example, should there be a significantly greater amount negativity in election campaigns in Washington, one of the most polarized states, one could attribute the differences in urban and rural population to be a variable that drives up both negativity and polarization. That is, because urban and rural populations can have very different jobs and live in different geographical areas, it is more likely to spawn the tribal us-vs-them mentality due to these factors than to partisan identity. In addition, different kinds of policies are wanted by people that lead different lifestyles, so the difference in policy preference also drives up polarization. Therefore, should there be a statistically significant relationship between polarization and negativity, the correlation could be due to the demographics of the state. However, one could also argue that nearly every state has major cities and rural areas — if demographics is really driving both factors, then we should expect little variation of polarization and negativity across most states.

6 Data & Variables

6.1 Dependent Variable - Campaign Negativity

To obtain the tweets from the 2014 gubernatorial candidates, I first scraped the Wikipedia article [1] to obtain metadata of all 142 candidates, including name, state, incumbency, and party. Then I manually collected the twitter handles of those who were active during the 2014 election. I chose to collect the campaign Twitter account if there are more than one account available for a candidate. To collect the tweet bodies, I use the Twitter API [2] to scrape all tweets from those twitter handles during three months leading up to the election.

My unit of analysis is candidates in the 2014 gubernatorial election. The dependent variable I measure in the study is campaign negativity for each candidate, measured in two ways: 1) the quantity of attack tweets, i.e. the proportion of the attack tweets amongst all tweets in a candidate's Twitter timeline, and 2) their viciousness, i.e. the amount of negativity in a candidate's overall tweets.

Measuring the viciousness of a tweet calls for a new indicator index, the Political Tweet Viciousness Index (PTVI) [3]. To measure campaign negativity, previous liter-

[1] 2014 United States gubernatorial elections: https://en.wikipedia.org/wiki/2014_United_States_gubernatorial_elections?oldformat=true

[2] Brendan Brown's Twitter Scraper: https://github.com/bpb27/twitter_scraping

[3] This paper defines negativity as the degree to which the content attempts to disrupt the opposition instead of civilly contribute to the debate of policy and share useful information to the voters. Instead of categorically place a political tweet into a category, I place tweets on a scale of negativity. To score high on the negativity scale, the tweet contributes less to policy debate and

ature (Geer (2006)) measured appeals. Geer (2006) defined appeals as dichotomous: it's either positive, i.e. "any mention of a theme or reason to vote for one candidate", or negative, i.e. "any criticism or reason to vote against the opposition". The negativity of a given ad is measured by the proportion of the number of negative appeals over that of all appeals that appeared in that ad. However, this method of coding is time consuming and requires up-to-date knowledge of the political debates during the time period for analysis.

This study proposes a different indicator that takes three factors into account. Firstly, I make the assumption of the dichotomy of attack tweets — they are either an ad hominem attack or a policy attack (ad hominem v.s. policy). If it is an ad hominem attack, then the tweet does not give the voter any useful information about policy and presumably there is a vicious intention behind the attack. I count these tweets as vicious attacks. Within the vicious attacks, I consider if there is language used by the candidate that is associated with negative emotions. If it contains more negative sentiment words, then it is more vicious than the ones that contain less of these negative sentiment words (i.e. in Mohammad and Turney (2010)). On the other hand, if a tweet is not an attack tweet, or is an attack on policy position, I consider it a score of 0. A more detailed discussion of PTVI is presented in Section 7.1.

In comparison to previous work, both the PTVI and Geer (2006) index consider ad hominem attacks fall under a negative appeal, because it directly draws upon the shortcomings of their opponents; on the other hand, a policy would also fall under Geer (2006)'s negative appeals, but would not be scored in the PTVI. At the same time, the PTVI also considers the language itself by looking for specific words that associate with negative emotions. Admittedly, PTVI is a much more coarse grained index compared to Geer (2006)'s index — the latter allows for a more nuanced categorization of tweets. But PTVI allows for a more general index that's

is less civil. To compare to Geer (2006)'s definition, this scale highlights the difference between a policy attack and a personal attack. Because personal attacks are unlikely to reflect much about the ability of the opponent to govern or has anything to do with someone's ability to hold an office, it is therefore considered less civil and less useful than an attack on policy.

more invariant to time, and greatly reduced the time needed for human coders.

6.2 Independent Variables - Political Polarization

I will measure both party polarization and mass polarization by state. Shor and McCarty (2011) provide an indicator of party polarization. It takes into account the state legislature roll call records and survey data from the National Political Awareness Test (NPAT). With the indicator, one can use the roll call vote records to measure every state's partisan polarization (in the legislature) based on the ideological distance between the median legislators within the Democratic and the Republican parties. The greater the distance, the higher the polarization. They have made their measurements publicly available to download [4].

To measure the mass polarization effect, I use the Political Typology Survey study conducted by Pew Research Center *Political Polarization in the American Public* (2014). They surveyed over 10,000 people with questions asking their policy preferences and attitude towards partisanship. By separating self-identifying Republicans and Democrats' responses to these questions, I can measure the level of mass polarization in each state. To calculate the level of mass polarization per state, I calculated the difference between ideological medians of the self-identifying Democrats and Republicans. Their data is public available to download [5].

6.3 Control Variables

6.3.1 Incumbency

As previous literature suggest, incumbency affects the tendency of candidates to go negative (Evans et al. (2017); Evans, Cordova and Sipole (2014); Weber (2008); Lau and Pomper (2002); Trent, Friedenberg and Denton (2011)). To operationalize incumbency, I collected the candidate incumbency status from the Wikipedia article of 2014 gubernatorial elections. Incumbency is then coded as a binary variable with

[4] https://americanlegislatures.com/data/

[5] https://www.people-press.org/dataset/2014-political-polarization-survey/

0 representing a candidate is a challenger and 1 representing an incumbent. In the case of an open seat, I use 0 to code for all candidates in that race.

6.3.2 Competitive Races

The competitiveness of the race is given by Cook Political Report *2014 Governor Race ratings* (2014). I use a binary variable where 0 indicates a noncompetitive race and 1 indicates a competitive one.

6.3.3 Party Affiliation

To operationalize party affiliation, this study incorporates a binary variable: 0 indicates a Democratic Party candidate, 1 indicates a Republican Party [6]. The party affiliation is scraped from the Wikipedia page of the 2014 gubernatorial election.

6.3.4 Gender

To code for gender, I manually went through each candidate's biography on Wikipedia to identify their gender identity and coded with nominal variable that takes on 3 values: 0 representing female, 1 representing male [7].

7 Method

7.1 Automating PTVI

PTVI places tweets into three categories: non-attack tweets, policy attack tweets, and ad hominem attack tweets. However, it is time consuming and potentially expensive to code every single tweet by human coders. Therefore, I adopt an automatic coding pipeline with minimal human involvement.

To classify attack tweets from non-attack tweets. I use the metadata scraped from Wikipedia and assigned the set of opponents to each candidate. For each tweet, if

[6] This project focuses only on only the major parties, so third party candidates are removed.

[7] Note that there were no candidates in the 2014 gubernatorial elections identified as non-binary.

the text mentions the opponent's first name, last name, full names, or the Twitter handle, or the word "opponent", I classify that tweet as an attack tweet. I removed potentially ambiguous first/last names (e.g. "Bill" to disambiguate from a legislative bill). I also removed first/last names that are shared by multiple contestants in that state (e.g. Tom Wolf (D) v.s. Tom Corbett (R) in Pennsylvania). Human validation of 300 random sampled tweets showed that the method achieved 88.46% F1 score (95.83% precision, 82.14% recall, see Table 1). I found 13.09% of all tweets are attack tweets (see Table 2).

Then I used a dictionary method to classify policy tweets from non-policy tweet within all attack tweets. I first stemmed all tweet texts with NLTK Snowball stemmer [8] to remove morphological variations on words, and built a set of vocabulary ($|V|$ = 7150) within attack tweets. Then I picked top n = 2000 tokens ordered by their frequency of occurrence in descending order and hand-coded them into 1) token that strongly indicate the tweet contains it is a policy tweet, and 2) other tokens. For example, Category 1 include tokens such as "border", "climat", "gun" and hashtags "#raisethewag", "#vergara". In total, I found 65 policy tokens out of the 2000 tokens labelled. Next, I classified attacks tweets that include these tokens as policy tweets and attack tweets that are not policy tweets ad hominem attack tweets. My choice of n is justified by the diminishing return of labelling tokens. Figure 1 shows the proportion of policy tweets over attack tweets with respect to the number of tokens labelled. It demonstrates that once n > 500, the increase of policy token proportion starts to plateau. Therefore I can safely choose n = 2000. Human validation of 300 randomly samples tweets showed a F1 score of 91.67% (91.67% precision, 91.67% recall, see Table 1). I found 4.33% of all tweets are policy attack tweets (see Table 2).

7.2 Notes on Pennsylvania

In the analysis, I excluded the Pennsylvania gubernatorial race because it is an outlier to the assumptions I made following the previous literature. The Cook Political

[8] https://www.nltk.org/_modules/nltk/stem/snowball.html

Classification Type	Precision (%)	Recall (%)	F1 (%)
Attack-Nonattack	95.83	82.14	88.46
Policy-Nonpolicy	91.67	91.67	91.67

Table 1: The classification precision, recall, and F1 score in the 150 random sample.

Classification Type	Out of All Tweets (%)	Out of Attack Tweets (%)
Attack	13.09	-
Policy	4.33	36.12

Table 2: The proportion of attack tweets and policy tweets in the entire corpus.

Report indicates that the Democratic challenger Tom Corbett was going to defeat the Republican incumbent Tom Wolf with good confidence (*2014 Governor Race ratings* (2014)). Therefore, Pennsylvania race was non-competitive and the incumbent was projected to lose. In this case, we should expect the incumbent, Tom Wolf, to attack more than he would have if this was a race he was going to win. Therefore, Pennsylvania is an outlier because 1) it is a non-competitive that has relatively large number of attacks, and 2) the incumbent is going to tweet a lot of attacks. From Figure 2, we can see that Pennsylvania by far has the largest portions of attack tweets (over 40%, only followed by $\tilde{2}5\%$ from Connecticut). Because of all of these concerns, I decided to exclude Pennsylvania from the analysis.

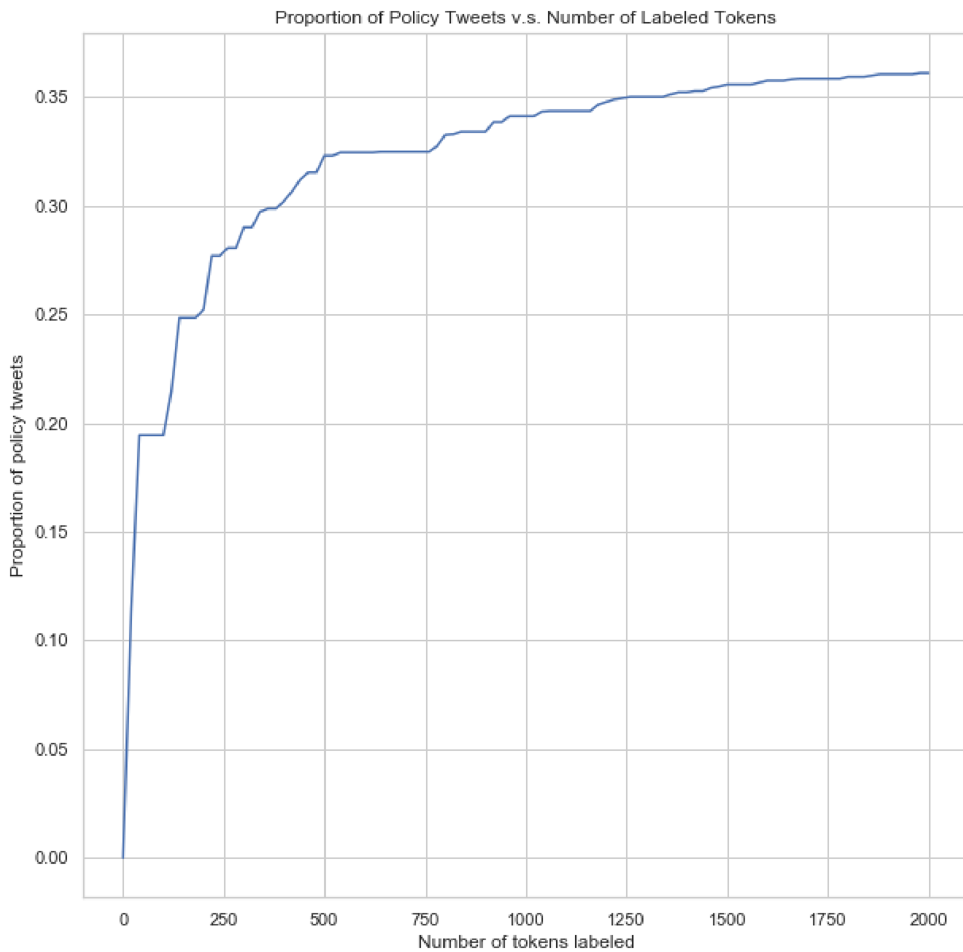

Figure 1: The number of policy tweets plateaus as more policy tokens are labeled. As I label more policy token, the number of tweets classified as policy tweet grows slower.

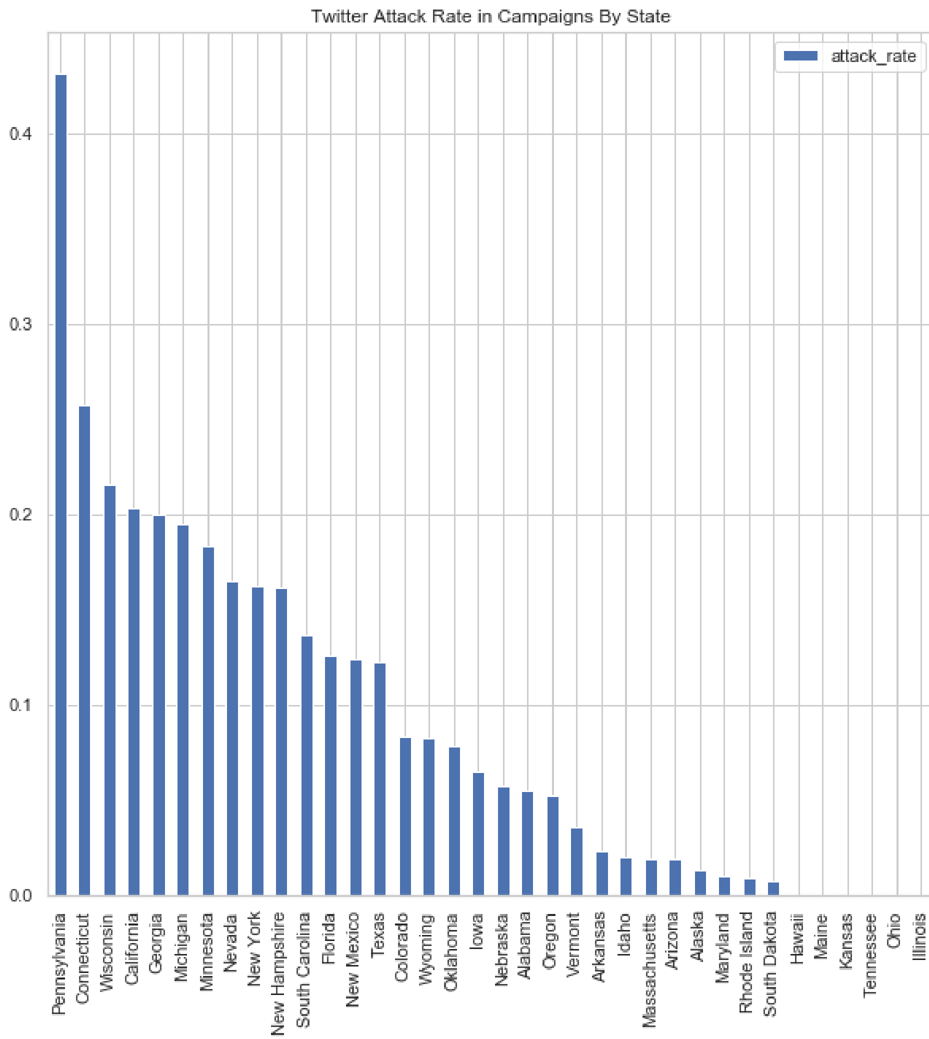

Figure 2: The attack rate of campaigns on Twitter. Pennsylvania leads by far and only has Connecticut trailing behind by nearly 15%.

7.3 Modelling

This study aims to examine the relationship between statewide party and mass polarization and the quantity and viciousness of 2014 gubernatorial candidates' attack tweets. To establish a causal relationship of increased campaign negativity as an effect of political polarization, I run 2 sets of multivariate regression models. One set of the models addresses the bottom-up causal mechanism that I put forth in the Section 5, and the other set address the top-down causal mechanism.

7.4 General Model Setup

The models are the combinations of 2 dependent variables and 2 independent variables. The first dependent variable is the percentage of attack tweets over all of the candidate's tweets, while the other one is the average PTVI over all tweets. At the same time, there are 2 independent variables: the continuous party polarization indicator in the state legislatures measured by Shor and McCarty (2011) and the continuous mass polarization indicator in different states measured from Pew Research Center's *2014 Political Polarization Survey* (2014). To rule out spurious factors, these models also share 4 control variables: a binary variable for incumbency, a binary variable for competitive races, a binary variable for party affiliation, and a binary variable for gender. For the purpose of this study, a p-value less or equal to .05 indicates significance, otherwise I will conclude the data failed to show a statistically significant relationship between either kind of polarization and the quantity and viciousness of campaign attack tweets.

7.5 Top-down Models

I plotted the graph of the level of elite polarization against PTVI with control variables to investigate any interactions between the independent variable and the control variables (Figure 3). Elite polarization (legislature ideological distance) is defined as the sum of House ideological distance and the Senate ideological distance for each state. The most important controls that interact with the ideological distances are party and incumbency. We see patterns that are inline with previous literature – incumbency rarely attack while challengers do. In Figure 3, we see that the PTVI from incumbents does not increase as ideological distance increases, but the PTVI from non-incumbents does. This indicates an interaction. At the same time, we see the PTVI from the Democrats does not increase as ideological distance increases, while it does for the Republicans. Again, this indicates an interaction. Therefore, I come up with the following linear top-down model: PTVI ~ideological_distance * incumbency * party + competitiveness + gender.

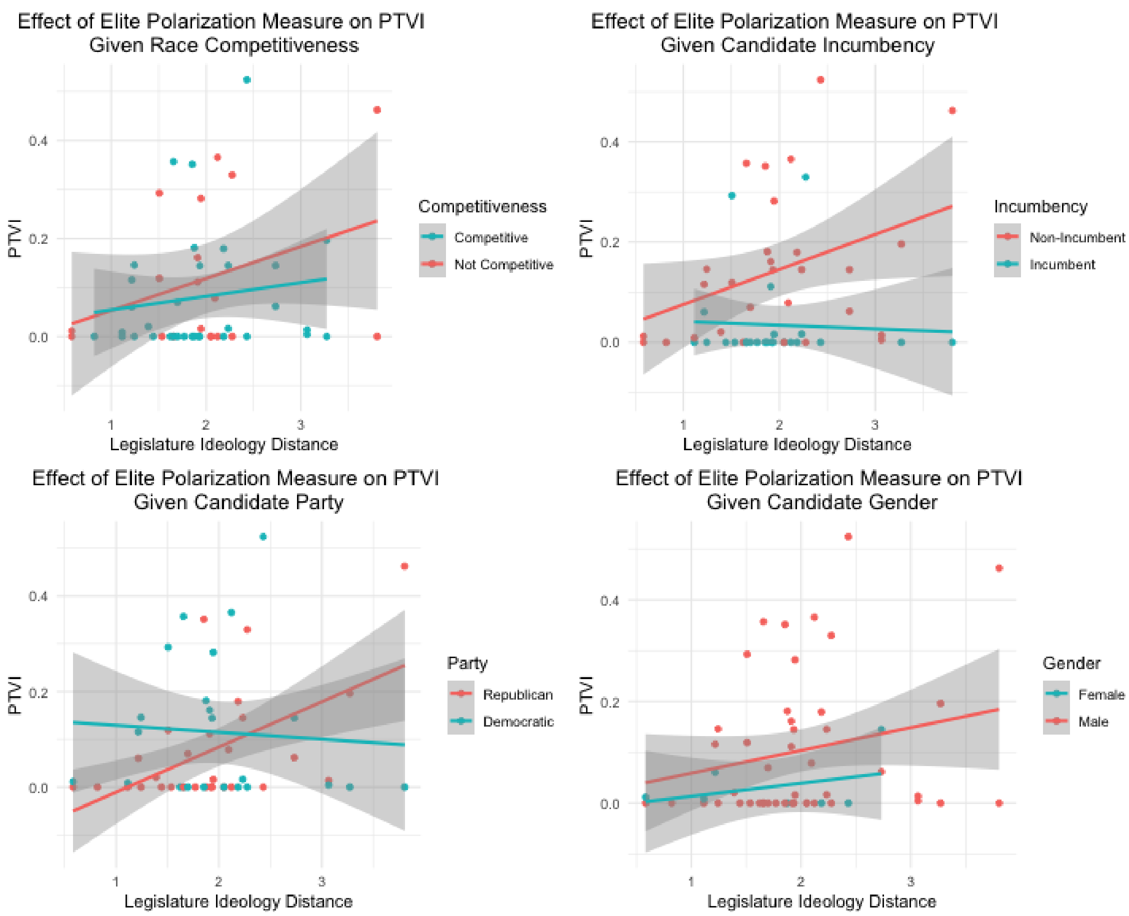

Figure 3: The top-down model given the 4 control variables.

7.6 Bottom-up Models

Similar to the top-down model, we see interactions between the mass polarization (public partisan distance) and incumbency, party, and race competitiveness (Figure 4). Therefore, I come up with the following linear bottom-up model: PTVI ~ideological_distance * incumbency * party * competitiveness + gender.

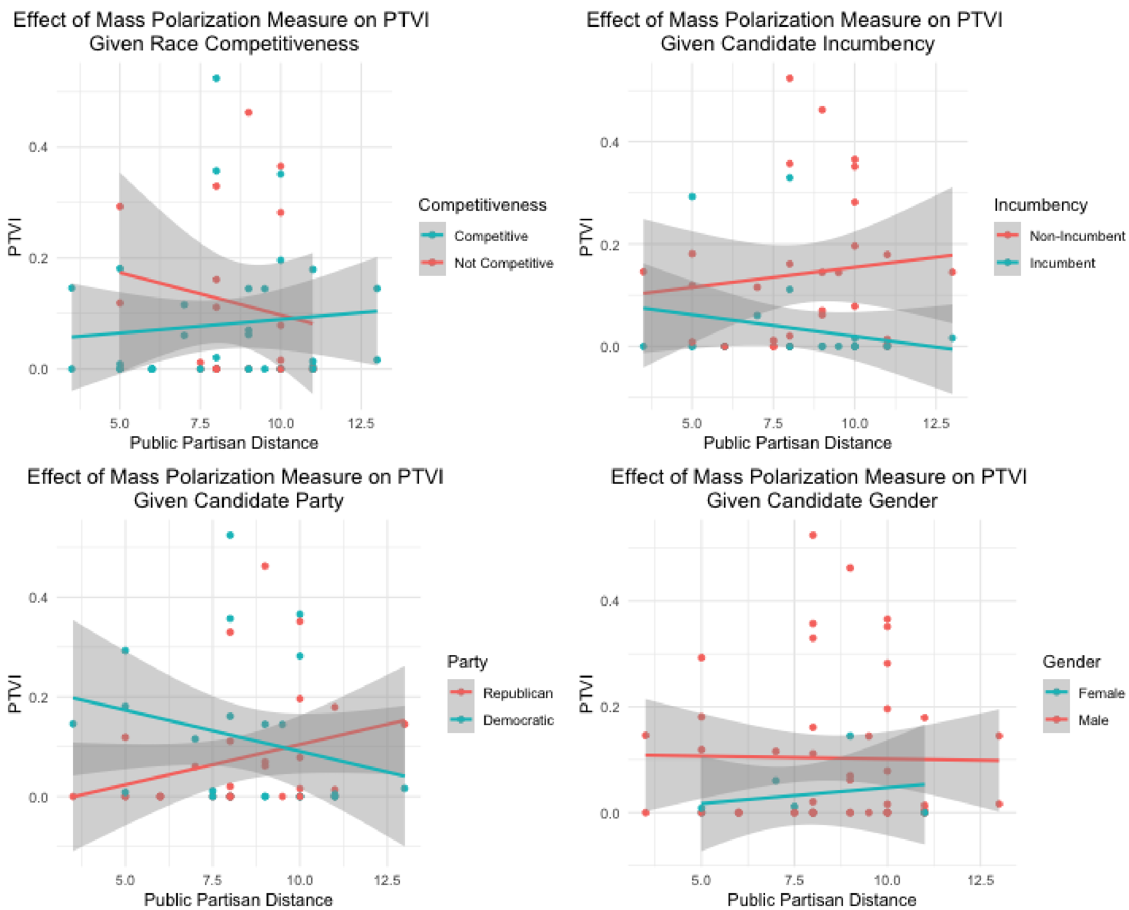

Figure 4: The bottom-up model given the 4 control variables.

8 Results

8.1 The Different Effects of Elite and Mass Polarization on Campaign Viciousness

The relationship between PTVI and the legislature ideological distance is significant taking into account for the control variables and interactions (Table 3). There is a positive correlation between the independent and dependent variables with a coefficient of 0.086872 ($p = 0.0261$). The adjusted r^2 value for the entire model is 0.1758. Interestingly, there is no other variables that significantly influence the dependent variable.

On the other hand, as shown in Table 4, relationship between PTVI and the public ideological distance is not significant even after taking into account the control variables and interactions. Instead, there is a slight positive correlation between the variables with a coefficient of 0.0243170 ($p = 0.488$). The adjusted r^2 value is 0.06786. Again, none of the other variables are significant, either.

These results give evidence to Hypothesis 2a while failed to reject the null for Hypothesis 2b. Essentially, this is showing that polarization amongst the elites is a better predictor than polarization amongst the public to the level of viciousness in an election campaign, and the top-down model is a better model to show how the election candidates will strategize their attacks than the bottom-up model.

Table 3: Top-Down Models

	Dependent variable:	
	Attack Rate	PTVI
	(1)	(2)
Legislature Ideological Distances (Elite Polarization)	0.047^{*}	0.087^{**}
	(0.025)	(0.038)
Incumbency	−0.034	−0.006
	(0.115)	(0.177)
Member of the Democratic Party	0.058	0.128
	(0.087)	(0.135)
Race is Non-Competitive	−0.037	−0.032
	(0.024)	(0.037)
Gender is Female	−0.032	−0.049
	(0.035)	(0.054)
Legislature Ideological Distance * Incumbency	−0.011	−0.033
	(0.061)	(0.094)
Legislature Ideological Distances * Member of the Democratic Party	−0.023	−0.042
	(0.042)	(0.064)
Incumbency * Member of the Democratic Party	0.122	0.082
	(0.158)	(0.243)
Legislature Ideological Distances * Incumbency * Member of the Democratic Party	−0.060	−0.061
	(0.078)	(0.120)
Constant	0.027	−0.029
	(0.058)	(0.089)
Observations	53	53
R^2	0.322	0.318
Adjusted R^2	0.180	0.176
Residual Std. Error (df = 43)	0.080	0.123
F Statistic (df = 9; 43)	2.270^{**}	2.232^{**}
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 4: Bottom-Up Models

	Dependent variable:	
	Attack Rate	PTVI
	(1)	(2)
Public Partisan Distance (Mass Polarization)	−0.007	0.024
	(0.021)	(0.035)
Incumbency	0.193	0.623
	(0.304)	(0.495)
Member of the Democratic Party	−0.224	−0.132
	(0.294)	(0.478)
Race is Non-Competitive	−0.227	−0.100
	(0.222)	(0.362)
Gender is Female	−0.023	−0.039
	(0.036)	(0.058)
Public Partisan Distance * Incumbency	−0.024	−0.081
	(0.034)	(0.056)
Public Partisan Distance * Member of the Democratic Party	0.027	0.009
	(0.033)	(0.054)
Incumbency * Member of the Democratic Party	0.443	0.136
	(0.425)	(0.691)
Public Partisan Distance * Member of the Democratic Party	0.024	0.001
	(0.026)	(0.042)
Incumbency * Race is Non-Competitive	−0.124	−0.485
	(0.349)	(0.569)
Member of the Democratic Party * Race is Non-Competitive	0.386	0.420
	(0.336)	(0.546)
Public Partisan Distance * Incumbency * Member of the Democratic Party	−0.056	−0.015
	(0.048)	(0.078)
Public Partisan Distance * Incumbency * Race is Non-Competitive	0.008	0.057
	(0.040)	(0.065)
Public Partisan Distance * Member of the Democratic Party * Race is Non-Competitive	−0.043	−0.033
	(0.038)	(0.062)
Incumbency * Member of the Democratic Party * Race is Non-Competitive	−0.702	−0.486
	(0.544)	(0.885)
Public Partisan Distance * Incumbency * Member of the Democratic Party * Race is Non-Competitive	0.081	0.044
	(0.060)	(0.097)
Constant	0.164	−0.027
	(0.173)	(0.281)
Observations	53	53
R^2	0.426	0.355
Adjusted R^2	0.172	0.068
Residual Std. Error (df = 36)	0.080	0.131
F Statistic (df = 16; 36)	1.673*	1.237
Note:	*p<0.1; **p<0.05; ***p<0.01	

8.2 The Lack of Significance in Polarization's Effects on Attack Frequencies

For the attack frequency models, there is no significance found for either the top-down model or the bottom-up model. In the top-down model, there is a positive correlation between the attack frequencies and the legislature ideological distance with a coefficient of 0.04718 (p = 0.0601). This model reports a 0.1837 adjusted r^2 value. In the bottom-up model, there is a slight negative correlation between the variables with a coefficient of -0.007328 (p = 0.733). This model reports a 0.1715 adjusted r^2 value.

These results failed to reject the null for Hypotheses 1a and 1b. It indicates that the polarization amongst either the party elites or the public is not a good predictor of the frequencies that election candidates attack on their Twitter, which shows a stark contrast with the PVTI measure of campaign negativity. It suggests that polarization may have more to do with the substance and language of the negative tweets than the quantity of attack tweets itself.

9 Discussion and Future Work

The results shows the premise my top-down model is more likely to be in tune with the political reality – the effect of elite polarization positively influences the viciousness of the political campaigns. In states that have more divided legislatures, the political climate is a hostile one. Political elites adopt their group identities as partisans. To run a successful campaign, candidates tap into the partisan identities assumed by the current political elites, which normalizes vicious attacks on their opponent. Granted, running negative campaign is important when the opponent genuinely did something wrong or has proven to not deserve the public trust. When the offense is in fact serious, it is hard to imagine an attack tweet without rather vicious words. It is in the public interest to know such offenses when they go to the polls. However, my results suggest that when candidates viciously attack each other, sometimes it is simply attributed to political polarization rather than the serious offenses committed by their opponents.

In the Section 7.3, I added party and incumbency as interaction terms to the top-down model and added party, competitiveness and incumbency as interaction terms for the bottom-up model. Here I will lay out why made these choices and how do they play a part in the bigger picture. Firstly, as I pointed out earlier, incumbents in general rarely attack (See Section 6.3.1). To attract voters, they hold the advantage of being able to show a track record of political accomplishments in office. On the other hand, the challengers attack the track records of the incumbents to show that they will challenge the status quo and do a better job. Therefore naturally the challengers' campaign are more susceptible to the effect of polarization. Second, the graphs (Figure 3 and 4) show that Republicans candidates are more susceptible to the effect of polarization than Democratic candidates. Admittedly, it is not clear why this is the case or will this generalize to other elections beyond this election. It is clear, nonetheless, that in this election, the party identification plays a large role in the viciousness of the campaigns. Lastly, in the bottom-up model, there is an interaction term with the competitiveness of the race. In competitive races, there is an upwards trend on mass polarization positively correlating to the viciousness of the campaign; however the trend is not present in non-competitive races. This trend follows the expectation I set in Section 6.3.2, where in non-competitive races, neither the incumbent or the challenger has an incentive to attack – only the races are closer, the candidates need to make every bit of votes they can get. It is, however, surprising that the effect of competitiveness did not show up in the top-down model. In the top-down model, both competitive campaigns and non-competitive campaigns are affected by effects polarization have on campaign viciousness.

In Section 7.2, Pennsylvania was removed due to it being an outlier. The incumbent was going to be defeated, so it created a non-competitive race where the incumbents attacked a lot to boost his campaign against his challenger. This race intuitively goes against the model assumptions, therefore it was excluded. However, races like the one in Pennsylvania could potentially show an important pattern, which is campaigns attack the most when they are the incumbent and yet is projected to lose. While this goes beyond the scope of this paper, I encourage future work to incorporate this relationship into their model as well.

The results of this paper paints a rather bleak picture of the American political discourse during an election. Going forward, as America is becoming more divided amongst the party elites, we can expect more vicious attacks from candidates during an election. However, it is also important to acknowledge that this paper only examines 1 election on the state level. It is still unclear whether there is a similar trend in the federal level or across time. I encourage future work to explore this area because more and more data will be available as more election campaigns will be using Twitter as part of their digital platform to reach voters.

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