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2016 美國總統大選中的政治極化與輿情分析：以臉書資料為例

Political Polarization and Public Opinion on Facebook in 2016 US Presidential Election

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謝辭

三年時光，對一個法律系畢業的學生而言，要重拾久未接觸的數學、將程式語言從頭學起；要學習如何做研究、如何寫出好的論文。同時，還要回應別人對於自己在短短幾年內轉了三個領域的質疑，要面對每一個挫折時刻自己內心的徬徨，碩班的這段日子，並不好走。然而，我何其幸運，能在這一路上獲得許多幫助，跌跌撞撞著，也總算以這本畢業論文，給了這段日子自己的所有努力一個交代。

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摘要

Facebook 及推特等社群軟體的崛起，讓社群媒體上的政治行為備受重視。本文則聚焦在 2016 美國總統大選中，Facebook 上的政治極化現象與川普對於公眾輿論及議題設定的影響。本文使用 Facebook 上的使用者按讚資料，建立不同的意識形態極化指標來觀察 Facebook 上的政治極化程度，並進一步結合 FBI 的仇恨犯罪資料，探索對網路上的極化現象與現實世界中的犯罪行為間的關聯。此外，本文也試圖從 Facebook 資料中挖掘川普對於公眾輿論，特別是種族與移民議題上影響的證據。本文發現，Facebook 上的政治極化程度確實隨著競選過程而提高，同時與仇恨犯罪行為間存在正相關。另外，資料顯示川普對於移民與種族議題的言論對於媒體的議題選擇造成部分影響，同時我們也發現保守派與自由派間對於相關議題的獲取行為存在差異，特別是在移民議題上。然而，沒有證據顯示川普在移民及種族議題上對閱聽者的態度及議題偏好有所影響。

關鍵詞：政治極化、公眾輿情、社群媒體、仇恨犯罪、川普。

JEL 分類代號：L82、D72、C81。

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Abstract

Since social media platform such as Facebook and Twitter became popular among the world, the political behavior on social media has become a great interest of scholars. In this paper, we are interested in the level of political polarization and Trump's impact on public opinion and agenda setting on Facebook during 2016 U.S presidential campaign. We propose different indexes to observe the level of political polarization among users using an user-like data. In addition, combing with hate crime data from FBI, we explore the relationship between online polarization and offline hate crime behavior. We also seek for some evidence to show the impact of Donald Trump on public opinion toward immigration and racial issues on Facebook from our data. We find that the polarization level on Facebook did increase during the presidential campaign, with a positive correlation with hate crime numbers. Moreover, the data suggest that there are some impact of Trump on agenda building, and a polarization in attitudes toward our interested issues between conservatives and liberals, especially on immigration issues. However, there are no evidence showing that Trump has an impact on public attitude and first-level agenda setting.

Keywords: Political Polarization, Public opinion, Social media, Hate crime, Donald Trump.

JEL Classification: L82、D72、C81.

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Chapter 1

Introduction

As social media such as Facebook and Twitter is wildly used for people to share their life and thoughts ?, many people express their political opinion on social media, which stimulate research interests among political scientists. Other than mass political preference and opinion, scholars have studied the connection between online and offline political behavior, especially political participation such as voting behavior. Barberá and Rivero (2015) studies the representativeness of users on Twitter, providing an implication for future research on the relationship between social media and politics. Bode (2012) and Bekafigo and McBride (2013) focus on the relationship between voting and online political behavior using Facebook and Twitter data respectively. Nowadays, studying political behavior on social media has become an important field due to the accessibility of data and its linkage with offline behavior.

In addition to playing an important role in political behavioral studies, the advantage in large amount of texts and variety in issues make social media become a popular wind vane of public opinion toward particular issues. O'Connor et al. (2010) and Bollen et al. (2011) shows that the sentiment and mood states of tweets is highly correlated to the public opinion measured in survey data. Moreover, the common usage of social media platform has changed mass information consuming behavior. In this so called "new media era", social media platform has become a main resource of information consumption, forcing medias and politicians nowadays to pay a huge attention on information offerings on these platforms. Therefore, the agenda setting on social media also remains an interesting research question.

The 2016 U.S. presidential campaign is now a popular research object due to the rise of an unconventional candidate, Donald J. Trump. Considered as a division line between partisans in the United States and the disgraceful history of discrimination, immigration and racial issues have long been a taboo topic in political campaigns. However, Trump not only broke the line by bringing

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these issues to the table, his controversial and unfriendly expressions toward immigrants and blacks also raised a discussion on main stream medias. Did this kind of impact on agenda setting also appears in social media? And how did it affect the consumption of information related to the two issues? Moreover, the ability of Trump on shaping public attitude also remains a interesting research question.

In addition, the hatred between Republicans and Democratics was also found more severe during the campaign, along with a polarization in voting behavior. Schaffner et al. (2016) suggested that the racism in 2016 campaign is impactful in predicting support for Trump among white voters, implying that the extreme stance of Trump on opinion spectrum may make him attractive to those with similar thought. Exploring evidence to Trump's attraction to users on social media is also interested in this paper.

In this paper, we are mainly interested in the level of political polarization and Trump's impact on public opinion on Facebook during 2016 U.S presidential campaign. Different from the studies before, we use a Facebook data containing every posts and user reactions in 2015 to 2017 from U.S. politicians and 1000 pages mentioning Trump and Clinton during the campaign. We propose a polarization index based on an ideological measure of users and pages estimated by dimension reduction. We also explore the polarization level on Facebook in different aspect, including difference of ideological composition of presidential candidates' followers, and the ideological segregation on both pages. In addition, We then discuss the interaction between online and offline political behavior by exploring the relationship between online polarization index and hate crime behavior.

For the public opinion toward immigration and racial issues [1] on Facebook, we focus on four different dimensions to explore the impact of Trump on agenda setting and public attitude on Facebook: Media Volume and fan pages as supply side, and users' liking and commenting behavior as demand side. The exploratory analysis in this part aims to provide some evidence to the correlation between Trump's behavior and information supplying/consuming behavior during 2016 campaign from our data.

This thesis proceeds as follows. Chapter 2 reviews the literature. Chapter 3 proposes the polarization index along with the comparison with other segregation index. Chapter 4 discusses the relationship between hate crime behavior and online polarization. Chapter 5 shows the analysis of online public opinion toward immigration and racial issues. Chapter 6 concludes and discusses possible future works.

[1] In this paper, we defined those related to Muslim, Mexican immigrants, immigration, and illegal immigrants as immigration issues. The racial issues here are particularly the ones related to white and black.

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Chapter 2

Literature Review

In this chapter, we briefly review some literature related to our paper, including social media, agenda setting, Trump's influence, and hate crime analysis, and discuss the difference between this paper and past literature.

2.1 The Role of Social Media in Political Behavior

The increasing amount of users on social media nowadays attracts researchers' attention. The rich information of users' action such as page-following, commenting and connecting with others makes social media a important resource of studying political behavior. Kushin and Yamamoto (2013) and Bode et al. (2014) both studied the impact of social media usage on political participation and decision making, and provided some implication of how social media affect people's political behavior. Literature such as Bode (2012) and Bekafigo and McBride (2013) then focus on the relationship between voting and online political behavior. They both found some evidence of people's behavior on social media, including information consumption and social networking, affecting their voting behavior.

2.2 Agenda Setting

Agenda setting have long been an important issue in political campaign. Past literature payed a lot attention on the relationship between agenda setting and electorates' voting behavior, such as Roberts (1992), Abbe et al. (2003) and Sheafer and Weimann (2005). Other than the impact of agenda setting on electorates, the interaction between mass media and politician is also considered interesting for researches. Walgrave et al. (2008) studied the relationship between mass media,

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parliament and government in Belgium from 1993 to 2000, finding that media do to some extent determine the agenda of Parliament and government. On the other hand, Kiousis et al. (2006) explored the role of candidate news releases, media content, and public opinion in shaping the salience of political issues and candidate images.

Lightly different from the literature above, we focus on the interaction between media and presidential candidate, particularly Donald Trump, on Facebook during 2016 campaign. To be more precisely, we are interested in how media volume toward certain issues changed when Trump provided a related statement, and the reaction of users online during the campaign.

2.3 Political Polarization and Ideological Segregation

A common used measure of political polarization is DW-Nominate scores proposed by **?**, using recorded votes in the U.S. House of Repre- sentatives and the U.S. Senate to to categorize elected officials on an ideological scale from liberal to conservative. However, this measure can only capture the polarization level within political elite, being limited when it comes to mass polarization. Iversen and Soskice (2015) then uses a survey approach to estimate the proportion of polarized electorates by asking if the respondent recognized him/herself as a median voter.

Gentzkow and Shapiro (2011) used a completely different approach from the above. Instead of focusing on the segregation level between different political parties or issues, they provided a measure of the segregation on media consumption using online news data. Halberstam and Knight (2016) then focused on the role of homophily in information diffusion on social media using twitter data, and suggested that users are disproportionately exposed to like-minded information, which may increases the online segregation level.

There are also a few studies focusing on polarization on social media. Bakshy et al. (2015) explores the polarization level on Facebook in the aspect of exposure to ideologically diverse news and opinion. Gruzd and Roy (2014) suggests that there are pocket of political polarization on Twitter by observing the clustering effect around shared political views among supporters of the same party. Conover et al. (2011) identified the polarization phenomenon by the fact that the network of political retweets exhibits a highly segregated partisan structure, with extremely limited connectivity between left- and right-leaning users. Garimella and Weber (2017), also using Twitter data, suggested that there is a long-term increase in polarization on Twitter in the following three dimensions: Network, tweeting behavior, and content.

In this paper, we discuss the polarization level on Facebook, based on the liking behavior of users. Different from the literatures above, we focus on an ideology aspect, including mass ideo-

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logical polarization and the difference of ideological composition between presidential candidates' followers.

2.4 Trump's influence on public opinion and mass polarization

Studies of Trump' s influence on public opinion and mass polarization has become a popular topic since the 2016 presidential campaign. Flores (2018) explores the relationship between Trump' s campaign speech and public opinion toward immigrants using Gallup Survey Data and further conduct an experiment to test the impact of political elite on public opinion toward controversial issues such as immigration. Abramowitz and McCoy (2019) and Jacobson (2016) both argue that Trump' s campaign induced mass political polarization since it exploited divisions within the electorate in the United States. Also, the 2016 presidential campaign reinforced the rise of negative partisanship in the US.

In this paper, we are also interested in the topic of Trump's influence on public opinion, especially on immigration and race, and mass political polarization. However, we will focus on the online social media platform instead of the real world, using a data science approach which is totally different from past literatures.

2.5 Motivation of Hate Crimes

Previous studies on economic analysis of hate crimes mainly focus on the relationship between individual socioeconomic status and hatred behavior. Krueger and Malečková (2003) explores the causal effect of poverty and education on hate crimes and terrorism. Dharmapala and McAdams (2005) further provide a theoretical framework to analyze the influence of hate speech on behavior.

Other than the studies above, there were also some studies exploring the correlation between online behavior and hate crime. Chan et al. (2016) discussed the relationship between internet availability and hate crime, while Cohen-Almagor (2018) shows the positive relationship between online hate speech and hate crime.

However, there were few research focusing on the relationship between online political behavior, especially ideological polarization on social media, and motivation biased crime behavior. In this paper, we will introduce a state-level polarization index to explore the correlation between online polarization and hate crime behavior.

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Chapter 3

Ideological Segregation on Social Media

In this chapter, we explore the mass polarization level on Facebook in three different dimensions. First, we propose a ideological polarization index based on the ideological estimation using Facebook user-like data. Next, we analyze the difference between ideological composition of Trump and Clinton's followers. We also introduce the segregation index proposed by Gentzkow and Shapiro (2011), and discuss the segregation level on the two candidates' pages.

3.1 Data

In this paper, we use Facebook data from May 2015 to November 2016, including all fan pages of current national politicians, containing members and candidates of the Senate, the House, and the past and present Governors. Our data also includes the most popular 1000 pages that have ever mentioned the two major presidential candidates: Donald J. Trump and Hillary Clinton, in August 2016, selected by the total number of likes, comments, and shares of candidate-related posts in these pages. The data can be separated into three parts: User-like, post, and comment data.

User-like data in our data set records each users' liking behavior on the posts released by the fan pages mentioned above. We only consider those ever reacted on a national politician's fan page, which is defined as US potential users, to avoid those from other country. Post data includes every posts' information, containing post content, reaction, created time and created page. Comment data are similar to post data, which includes all the comments and their information reacting to the posts including in post data.

In this chapter, we'll use user-like data to construct an ideological segregation estimation. Then we'll further analyze post and comment data in chapter 5.

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3.2 Ideology Estimation

3.2.1 Using Dimension Reduction to Estimate Ideology Score

Spatial model in rational choice theory has been long used in the field of political behavior. The idea is that people will tend to support those that are closer to themselves on ideological spectrum. Following this concept, we assume that Facebook users tend to like the posts of those fan pages that are closer to their own unobserved ideal point. Based on this assumption, we use a two-step procedure suggested by Bond and Messing (2015) to obtain the ideological estimation.

To apply the method mentioned above to our data, we first construct an affiliation matrix by users' reaction, with the diagonal elements representing the number of unique fans [1] of each page, and the off-diagonal elements representing the numbers of shared-fans between pages. Then we transform the affiliation matrix A to agreement matrix G where $g_{ij} = a_{ij}/a_{ii}$. By viewing rows as observations and columns as features, each elements represent the similarity between the feature and related observation. The agreement matrix thus captures the embedded information between users.

After getting the agreement matrix, we conduct Principal Component Analysis on it for dimension reduction in order to obtain a more explanable measure with a lower dimension while preserving the original information. The first principal axis represents the largest variation within the agreement matrix, which is the followers shared by two fan pages. Exactly speaking, those that are closer to each other on the first principal axis implies that there are a larger overlapping between their followers. Recall that users will like those fanpages with similar ideological position to themselve, we can infer that fanpages that share a larger amount of users are closer to each other on ideological spectrum. Therefore, we simply interpret the first principal axis as ideology scores of fan pages.

With the ideological estimation of each fan pages, we can obtain users' ideology score by calculating the sample means of pages users like.

3.2.2 Ideological Dynamics

To estimate dynamic ideology scores, we use the data with a moving window of 4 weeks that updates every week. In particular, for a given week w_i, the data used to estimate the ideology score of the given week will be w_i to w_{i+3}. The reason why choosing 4 weeks as our time window instead of using only one week data is due to matrix sparsity problem. If there is only one week data used, the

[1] If a user likes at least one post from the page in a given period of time, the user is defined as the page's fan.

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constructed affiliation matrix will be quite sparse and therefore make our estimation biased.

Although choosing 4 weeks as time window can somehow solve the problem of matrix sparsity, there are also some disadvantages there. The most serious one may be the fact that the ideology estimation of a given week can't really represent the political attitude of the users in that week well, since there are another 3 weeks data used for estimation. This becomes an issue when we try to build a causal relationship between political attitude and other interested political behavior using these estimated scores. This is a trade off between estimation accuracy and representativeness. However, since we focus more on long term trend and the relative difference between week and week, the ideological dynamic can still provide some useful information.

Figure 1 shows the time series of mean and standard deviaton of users' ideology score. As we can see, the standard deviation increases while the election day approaches, implying that users' political attitude tends to become more polarized when the election gets colsed. This is quite intuitive since political campaign may induces political polarization within the electorates according to Hansen and Kosiara-Pedersan (2015). [2] On the other hand, there are no clear trend of the mean.

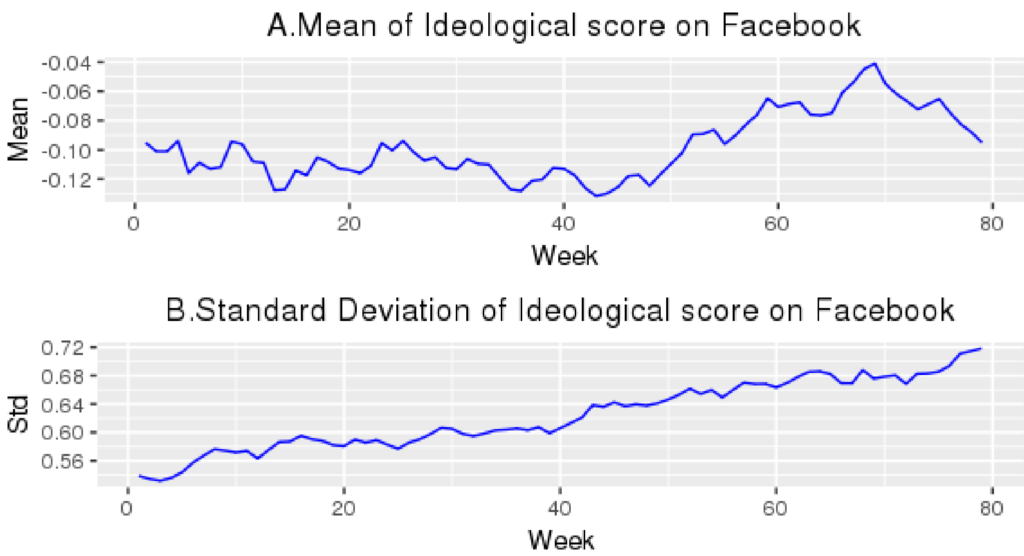

Figure 1: Time Trend of Ideological Distribution

[2] Hansen and Kosiara-Pedersan (2015) claimed that political campaign increases the affective distance between in-group party and out-group party preferences of electorates, and thus results in higher level of political polarization after campaign.

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3.3 Political Polarization on Social Media

3.3.1 Polarization Index

We are mainly interested in the difference between the two candidates' potential supporters. First, we classify the users into two groups through the process as follow: Given a user i and his/her ideology $\theta_{i,t}$ at week t, we define him/her as Trump's potential supporter if $|\theta_{trump,t} - \theta_{i,t}| < |\theta_{clinton,t} - \theta_{i,t}|$, vice versa.

Figure 2 shows the mean and standard deviation of two groups of users defined by the process above. The figure shows that Trump's potential supporters tends to become more "right wing" comparing to Clinton's potential supporters. Besides, the variation within both candidates' supporters increases during the political campaign.

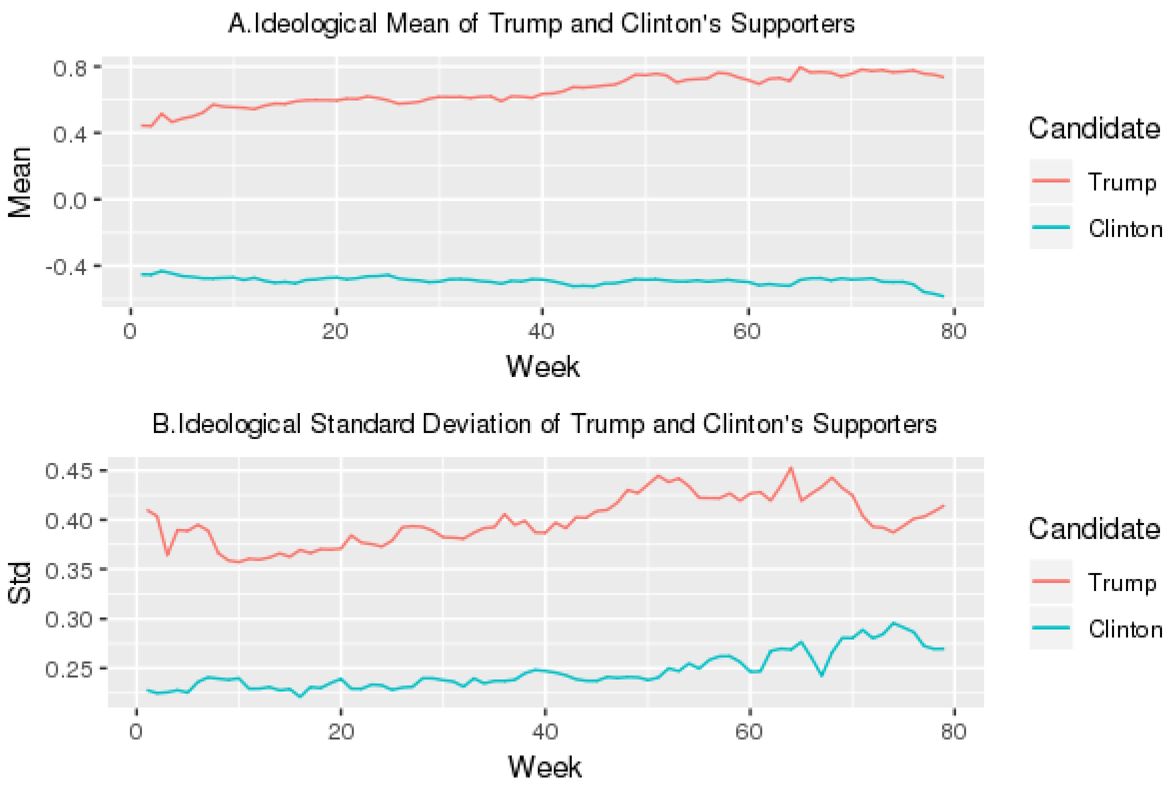

Figure 2: Ideological Distribution of Trump and Clinton's Potential Supporters

After separating users into two different groups, we then construct a simple index best representing the ideological difference between the two party. Following this concept, the index of ideological polarization η_t at week t is derived by calculating the mean difference of Trump and Clinton's supporters' ideology scores. Formally stated,

$$\eta_t = \theta_{i,t}^{tr\bar{u}mp} - \theta_{i,t}^{Cl\bar{i}nton} \tag{3.1}$$

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. Figure 3 presents the time trend of this ideological polarization measure [3]. From this figure, we can observe that the polarization index is increasing while approaching the election day. Figure 4 further shows the ideological distribution of the two candidates' supporters every three months from 2015/05/03 to 2016/10/26. We can find that the two distribution tend to become more separated, implying that the users on Facebook become more polarized, which is consistent with the polarization index.

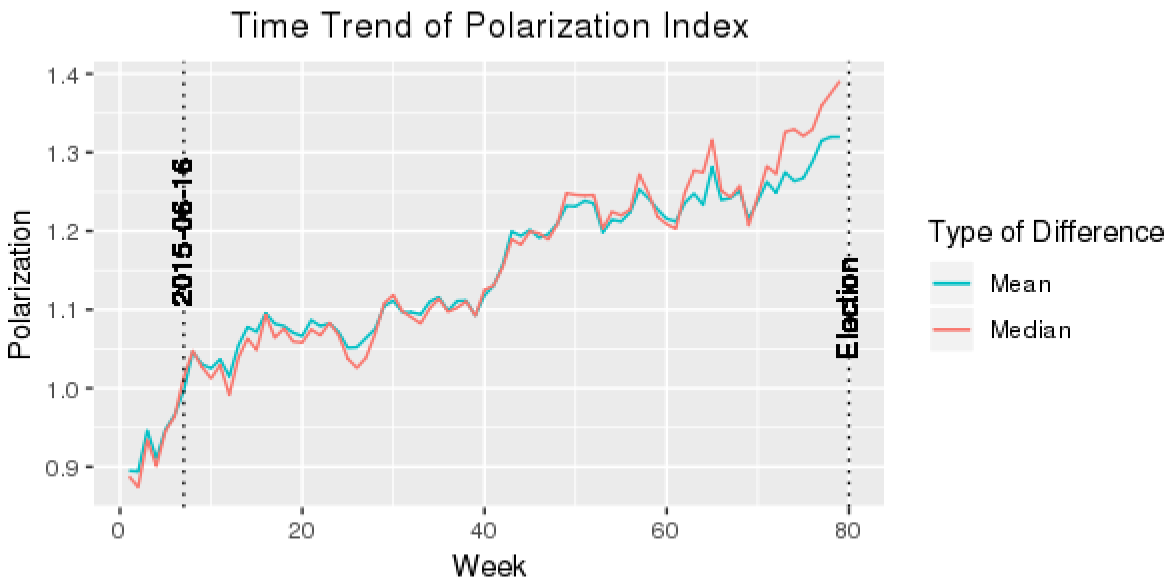

Figure 3: Time Trend of Polarization Index

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

[3] We also compute the median ideological difference of two groups and find there are no significant difference between the two.

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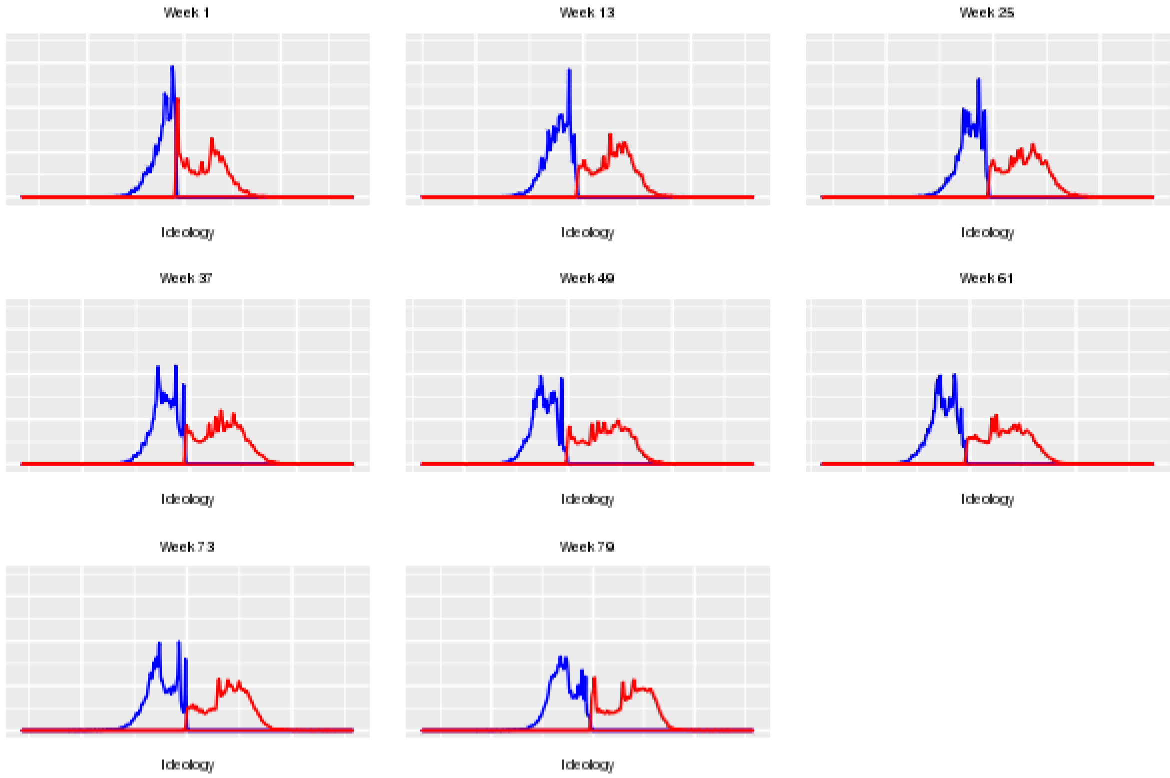

Figure 4: Changing in Ideological Distribution of Trump and Clinton's Potential Supporters

3.3.2 Polarization Index in State-Level

To further estimate the state-level ideological segregation, geographical information of the users is needed. We use each user's maximum likes of national politicians as a proxy of their true geographical information. To be more precisely, we calculate every user's like on each national politician. Then we sum the likes for those who come from the same state up, and compare the likes of each state. If an user likes the posts of the politicians from Texas the most, then the user will be defined as an electorate in Texas. Once the geographical proxy is constructed, we can simply apply the method above on users of each state to create the state-level ideological segregation index.

The basic idea of this method is that people tend to care more about those related to themselves. Since a politician from a given state is often viewed as a representative of the citizens, we assume that a user will tend to pay more attention on those representing themselves. However, there are some issues in this method. The most important one may be the fact that there are some politicians enjoying national popularity. They might have participated in the primary election of both party, such as Bernie Sanders in Democratic and Ted Cruz in Republican, or have been controversial for a long while. Due to their influence and fame, they are able to attract attention all over the nation, despite they are senators of certain states. Since this politicians often have lots of followers and are usually more active on Facebook, it will sometimes make our proxy become unreliable, especially

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on those who lives in smaller states with no famous politician.

Figure 5 shows the time trend of polarization index in conservative and liberal states [4]. All six states show an increasing polarization time trend during the campaign, regardless of population size and political leaning, consistent with the one shown in section 3.3.1

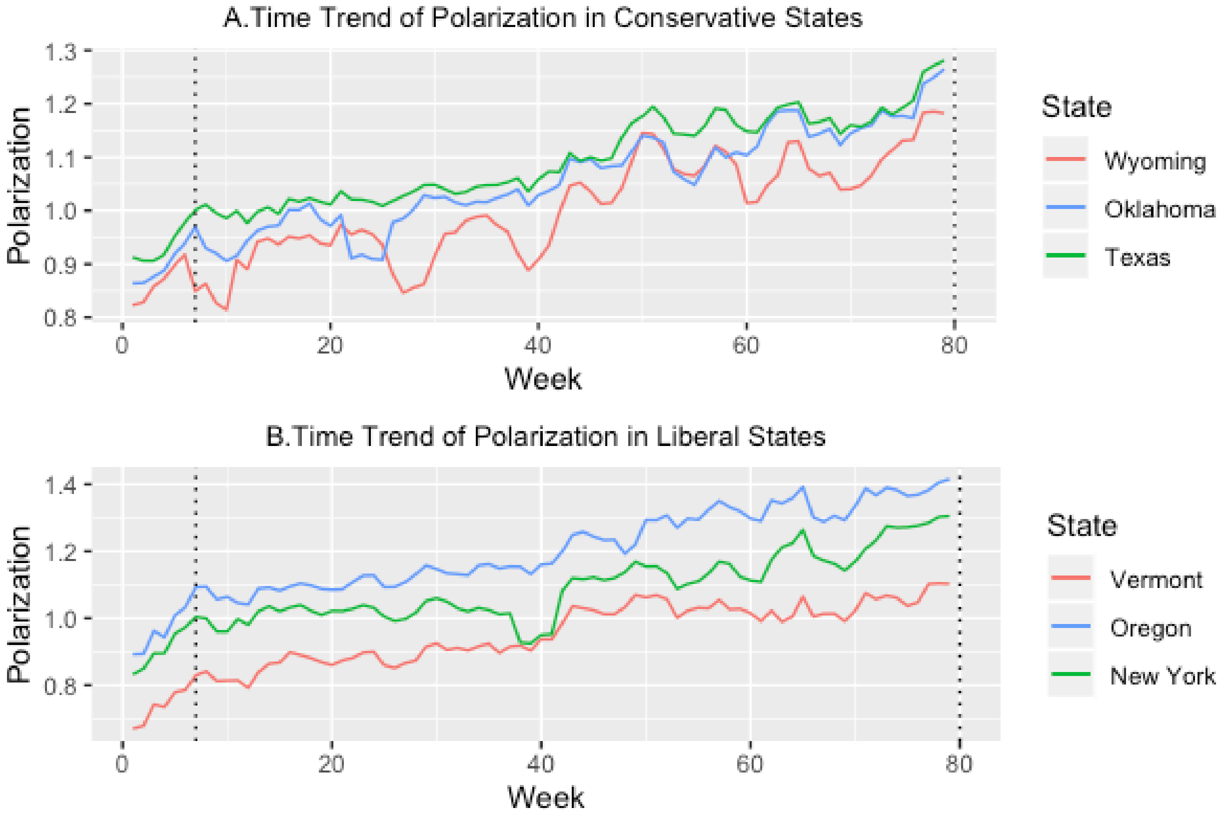

Figure 5: Polarization in Conservative and Liberal States

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

3.4 Tracking Trump and Clinton's Fans

We further analyze the users attracted by Trump and Clinton during the presidential campaign. In this section, we explore the amount of users attracted by the two candidates and the ideological polarization between both candidate's followers. We also focus on those newly attracted by the candidates with an extreme ideological position in each week.

[4] We select three states in small, medium, and large population size respectively in both groups.

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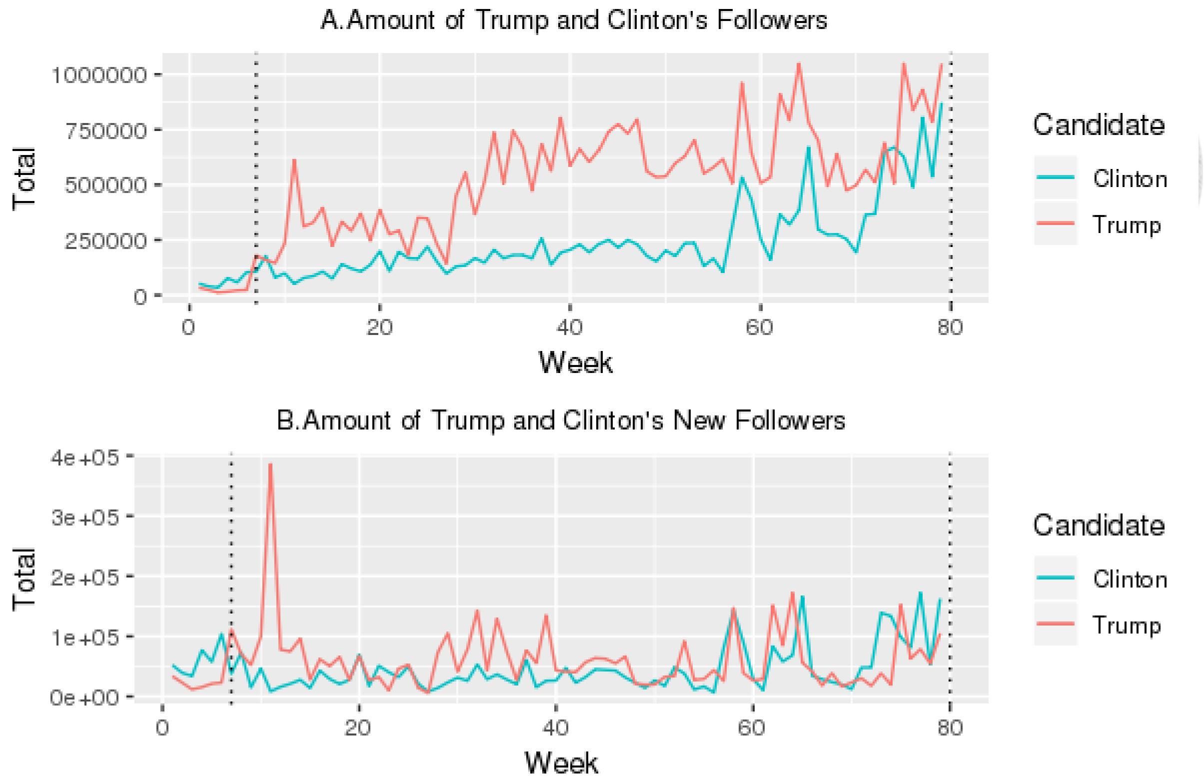

Figure 6: Amount of Trump and Clinton's Followers

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

3.4.1 Users liking Trump and Clinton's Posts

Figure 6A presents the amount of users liking the two candidates' posts each week, suggesting that both candidates gained more attention during the campaign while Trump seemed to be more attractive to users on Facebook. However, Figure 6B shows a small difference between the amount of users newly attracted by both candidates, implying that the stickiness of Trump's followers are stronger than Clinton's.

3.4.2 Ideological Polarization between Candidates' Followers

Figure 7 shows the time trend of ideological mean of two candidates' followers. From the figure, we find that the absolute ideological mean of Trump and Clinton's followers both increases during the campaign. In fact, the ideological mean of users newly attracted by Trump increases in a proportion of 92.1%, while the mean of those attracted by Clinton increases by 5%. Overall, the ideological mean of Trump's followers increases in a proportion of 133.7%, while Clinton's followers increases by 18.5%. The result suggests that users attracted by both candidates tend to be more extreme during the campaign. In addition, the ideology of original followers of candidates also deviate from median

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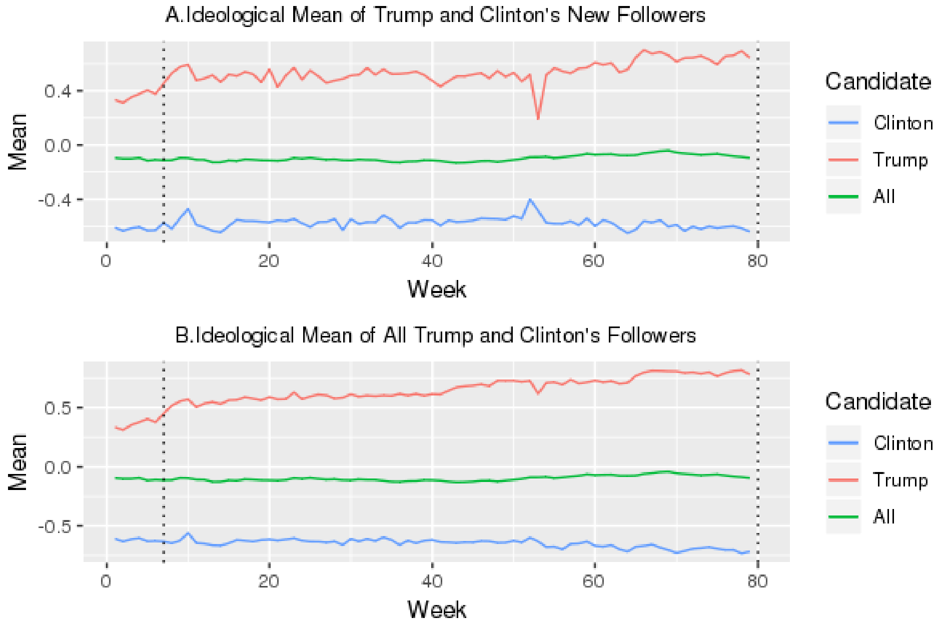

Figure 7: Ideological Mean of Trump and Clinton's Followers

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

during the campaign. This phenomenon appears to be more obvious within Trump's followers.

Figure 8 further shows the time trend of ideological polarization between Trump and Clinton's followers [5]. Consistent with the polarization index discussed in section 3.3.1, the polarization between Trump and Clinton's followers, including the newly attracted ones, increased during the campaign.

[5] The polarization index here is computed by the mean ideological difference of both candidates' followers.

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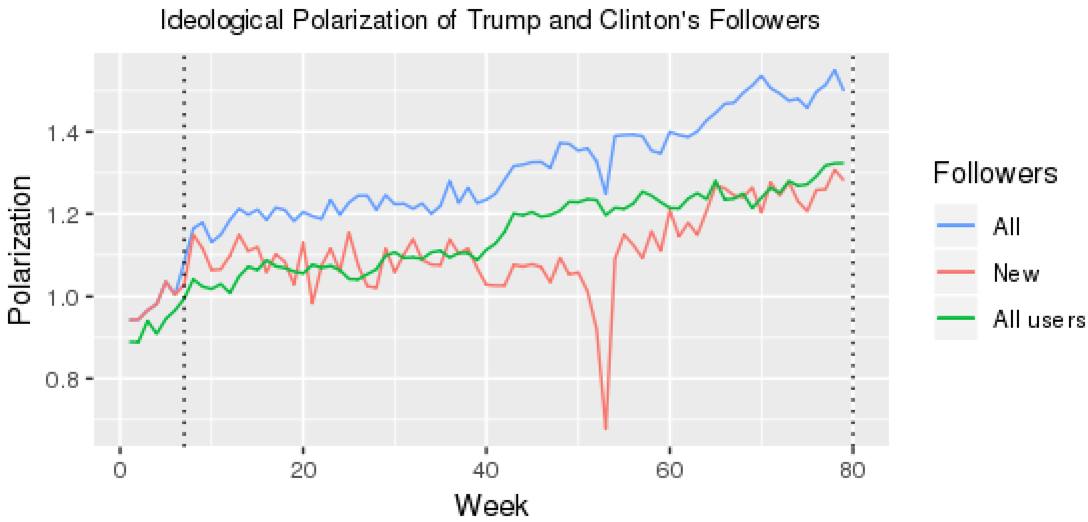

Figure 8: Ideological Polarization among Trump and Clinton's Followers

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

3.4.3 Far-Right/Left Politics Following Trump and Clinton

To explore the time trend of far right/left politics attracted by presidential candidates, we provide two definitions to identify those who are "extreme". First, we define those with an ideology score larger than 1 as far-right politics, and those with an ideology score less than -1 as far-lefts [6]. The other definition defines those with an ideology score falling outside of 2 standard deviation away from ideological mean in the whole distribution as extreme users, where those on the left defined as far-left politics, and those on the right defined as far-rights.

Figure 9 shows the proportion of far-right and far-left politics within the two candidates' followers. From the figure, we find that the proportion of far-right politics in Trump's new followers is higher than Clinton in both specification. This suggests that Trump is more attractive to extremest in the same political camp as him comparing to Clinton, which is consistent with the fact that Trump presented a more extreme stance on various controversial issues during the campaign. In addition, the ratio of extremest identified by the first definition within both candidates' followers increases during the campaign [7].

[6] The ideological distribution are centralized between -1 and 1.

[7] Due to the fact that the standard deviation of the ideological distribution increases during the campaign, the amount of users out of 2 standard deviation also declines.

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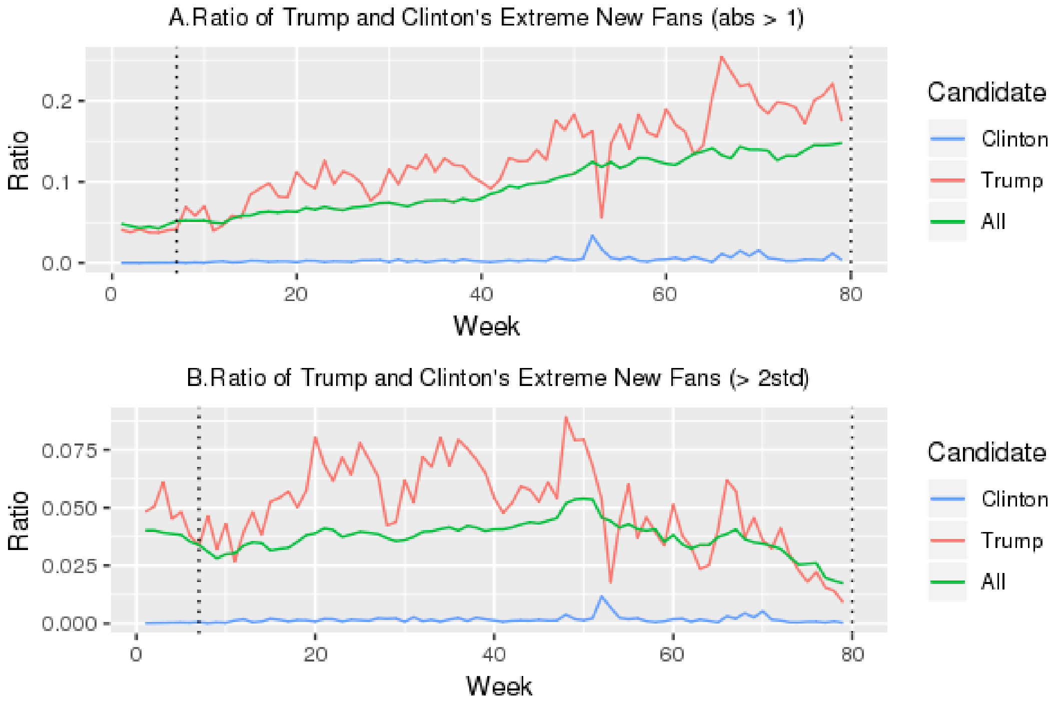

Figure 9: Ratio of Extremest in Trump and Clinton's Followers

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

3.5 Ideological Segregation on Fan Pages

In this section, we apply the segregation index proposed by Gentzkow and Shapiro (2010) on both candidates' pages, and observe the time trend of ideological segregation on fan pages.

3.5.1 Gentzkow and Shapiro's Measurement

Gentzkow and Shapiro (2011) provided an estimation of online isolation index, to measure the level of ideological segregation in online media. The index measures the difference between the news diets of conservatives and liberals. If what the liberals read are mostly liberals, and same as conservatives, the segregation level online will be really high since the both parties won't receive the news from the other. Following this idea, let m refers to media, j refers to an outlet such as CNN, New York Times, etc. Define $cons_j$ and lib_j to be the number of conservative and liberal visits respectively to outlet j, $cons_m$ and lib_m to be the total number of conservative and liberal visits on media m, and $visit_j$ and $visit_m$ to be the total visitors of outlet j and media m. The isolation index

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is measured by the formula below:

$$S_m = \sum_{j \in J_m} \frac{cons_j}{cons_m} \cdot \frac{cons_j}{visit_j} - \sum_{j \in J_m} \frac{lib_j}{lib_m} \cdot \frac{cons_j}{visit_j} \tag{3.2}$$

where $\sum_{j \in J_m} \frac{cons_j}{cons_m} \cdot \frac{cons_m}{visit_m}$ is the average conservative exposure, and $\sum_{j \in J_m} \frac{lib_j}{lib_m} \cdot \frac{cons_m}{visit_m}$ is the average liberal exposure to conservatives. This formula suggests that if conservatives and liberals both take the news holding a similar stance only, the isolation index will equal 1, which is the upper bound of the index.

3.5.2 Segregation on Trump and Clinton's Fan Pages

To apply this kind of measure on our candidates' pages, we convert it to the following version: For each week w_t, we separate the users into conservatives and liberals by the process mentioned in 3.2.2. We then extract users liking a post on Trump and Clinton's pages each week, and calculate the amount of conservatives and liberals within both candidates' followers respectively. We then estimate the segregation level S_{Tt}, S_{Ct} on Trump and Clinton's pages at week t using the formula as follow:

$$S_{Tt} = \frac{cons_{Tt}}{cons_{Ft}} \cdot \frac{cons_{Tt}}{visit_{Tt}} - \frac{lib_{Tt}}{lib_{Ft}} \cdot \frac{cons_{Tt}}{visit_{Ft}} \tag{3.3}$$

$$S_{Ct} = \frac{lib_{Ct}}{lib_{Ft}} \cdot \frac{lib_{Ct}}{visit_{Ct}} - \frac{cons_{Ct}}{cons_{Ft}} \cdot \frac{lib_{Ct}}{visit_{Ct}} \tag{3.4}$$

where $cons_{Tt}$ and lib_{Tt} are the amount of conservatives and liberals within Trump's followers at week t, and $cons_{Ct}$ and lib_{Ct} being the number of conservative and liberal within Clinton's followers at week t. In addition, $cons_{Ft}$ and lib_{Ft} are the number of conservative and liberal users liking a post in our dataset at week t, and $visit_{Tt}$, $visit_{Ct}$ represents the total follower of both pages.

Figure 10 shows the time trend of the ideological segregation index on Trump and Clinton's pages. The figure shows an overall time trend of an increasing segregation level on both candidates' pages during the political campaign, consistent with the trend of polarization index discussed in section 3.3.1 and 3.4.2. Moreover, the segregation level on Trump's page is larger than Clinton.

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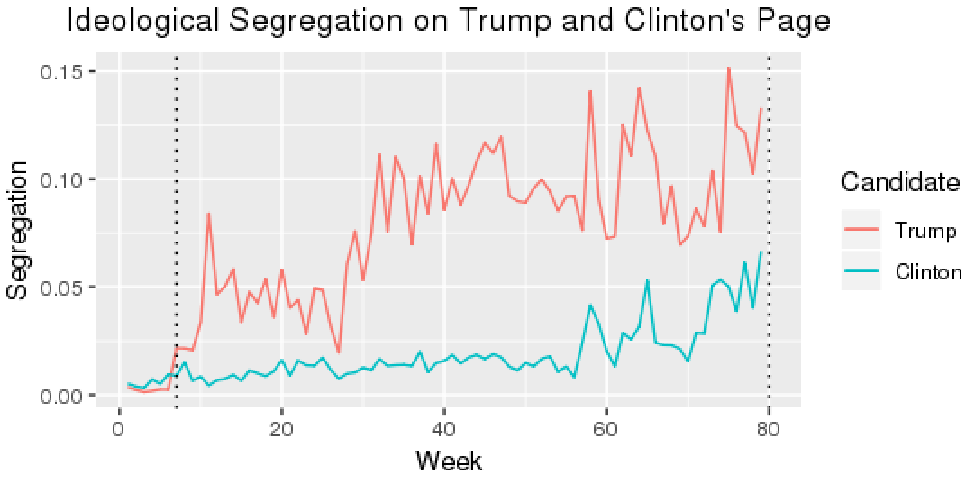

Figure 10: Time Trend of Ideological Segregation on Candidates' Pages

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

We further compute the average exposure of two type of users to conservatives and liberals on Trump and Clinton's page respectively. Figure 11 shows the time trend of both index. The figure suggests that the variation of segregation level is mainly determined by the average exposure of the political camp holding similar ideological stance with the candidates to conservatives/liberals. Besides, the average exposure of conservatives to conservatives on Trump's page is larger than the one of liberals to liberals on Clinton's page, implying that comparing to liberals, conservatives' consuming behavior on candidates' information is more concentrated than liberals.

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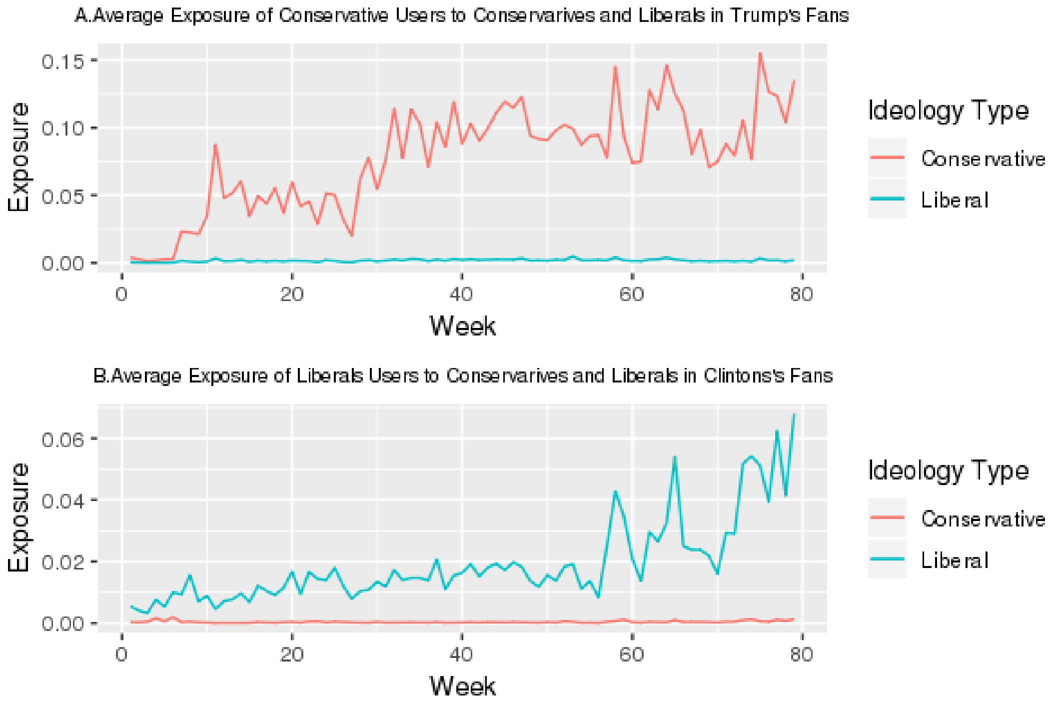

Figure 11: Average Exposure on Trump and Clinton's Pages

Notes: The first dash line represents the week Trump launches his campaign. The second dash line refers to the election week.

3.6 Discussion

The analysis results in this chapter provide some evidence of the increasing level of polarization on Facebook during the campaign. Section 3.3.1 presents an increasing time trend of ideological polarization between Trump and Clinton's potential supporters. Section 3.4 further suggests that there exists a similar trend when it comes to the ideological polarization between the two presidential candidates' followers, and section 3.5 shows that the segregation level on candidates' pages also increased during the campaign. These results implies that the increasing in mass polarization level among Facebook users not only appears in ideology aspect, but also exists in the consumption of candidates' information.

Moreover, the results in section 3.4 and section 3.5 both suggest that comparing to Clinton's attraction to liberals, Trump tended to be more attractive to conservatives, along with the far-right politics.

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Chapter 4

Interaction between Online and Offline Behavior: Hate Crime Analysis

In this chapter, we use the hate crime [1] incident reporting data from FBI and the polarization index introduced in section 3.2.2 to illustrate the relationship between online polarization and offline behavior.

4.1 Data

In this section, we'll give a brief introduction of our data, and take a quick look at the data by summary statistics.

4.1.1 Data Description

The hate crime incident reporting data used in this paper is collected by NIBRS [2] from 2006 to 2017, including six biases: race/ethnicity, religion, disability, sexual orientation, gender, and gender identity. The data provides useful information of each hate crime incident including reported date, state, reported agency, bias motivation, victims, offenders, type of offense and location type.

Due to the official manual provided by FBI, the data is collected by Two-Tier Decision-Making Process. The first level is the law enforcement officer who initially responds to the alleged hate crime incident. They are responsible for determining whether there is any indication that the of-

[1] Based on the definition of FBI, a hate crime is a committed criminal offense which is motivated, in whole or in part, by the offender' s bias(es) against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity.

[2] National Incident-Based Reporting System. The data from NIBRS provides information on victims, known offenders, relationships between victims and offenders, arrestees, and property involved in crimes.

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fender was motivated by bias. Once an incident is designated as a "suspected bias-motivated crime" , it will be forwarded to the second-level judgment office to review the facts of the incident and make the final determination of whether a hate crime has actually occurred. The incident will reported to the FBI UCR Program as a bias-motivated crime after the decision process.

Other than hate crime data, we also collected crime data from 2015 to 2017 in 35 states [3] from NIBRS Program. The data included information such as incident reported date, states, agency and type of offense. However, due to the fact that the data only contains a part of states in U.S., this data will only be used as a comparison, finding out whether there are any special time trend within hate crime data.

4.1.2 Summary Statistics

Figure 12 shows the time trend of number of (racial) [4] hate crimes from 2006 to 2017, where Figure 13 shows the time trend of crime from 2015 to 2017. Both figure shows a decrease in the frequency of both hate crimes and crimes in November, December and January, suggesting that there exists a season effect on criminal behavior. To be more precisely, the amount of crimes are on the decrease when the weather becomes more chilly.

Other than the season effect mentioned above, there are some other interesting implications from the data. First, the number of hate crime drastically reduced after 2008, the year when Obama, the first black president in the United States, took the power. We also observe that incidence of hate crime is higher in Republican era than Democratic one. This pattern provides some implication of the relationship between ruling party and hate crime. Since Republicans are considered more conservative on immigration and racial issue, the public attitude toward immigrants and minorities may be affected by political elites and therefore tend to be more polarized, causing the number of hate crimes to become higher.

Recalling that political campaign induces higher polarization level (Hansen and Kosiara-Pedersen, 2017), the increase in the amount of hate crime starting from 2015 along with the spike at November 2016 appears to be interesting. Moreover, this kind of tendency also appears in the polarization index discussed in section 3.3.1. The result suggests that there may exists some positive correlation between political polarization and hate crime, which will be discussed in the following section.

[3] The states included in crime data: Alabama, Arizona, Arkansas, Colorado, Connecticut, Delaware, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Massachusetts, Michigan, Missouri, Montana, New Hampshire, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin.

[4] Racial Crime includes Anti-Asian, Anti-Hispanic, Anti-Black, Anti-American Indian or Alaskan, Anti-Other ethnicity.

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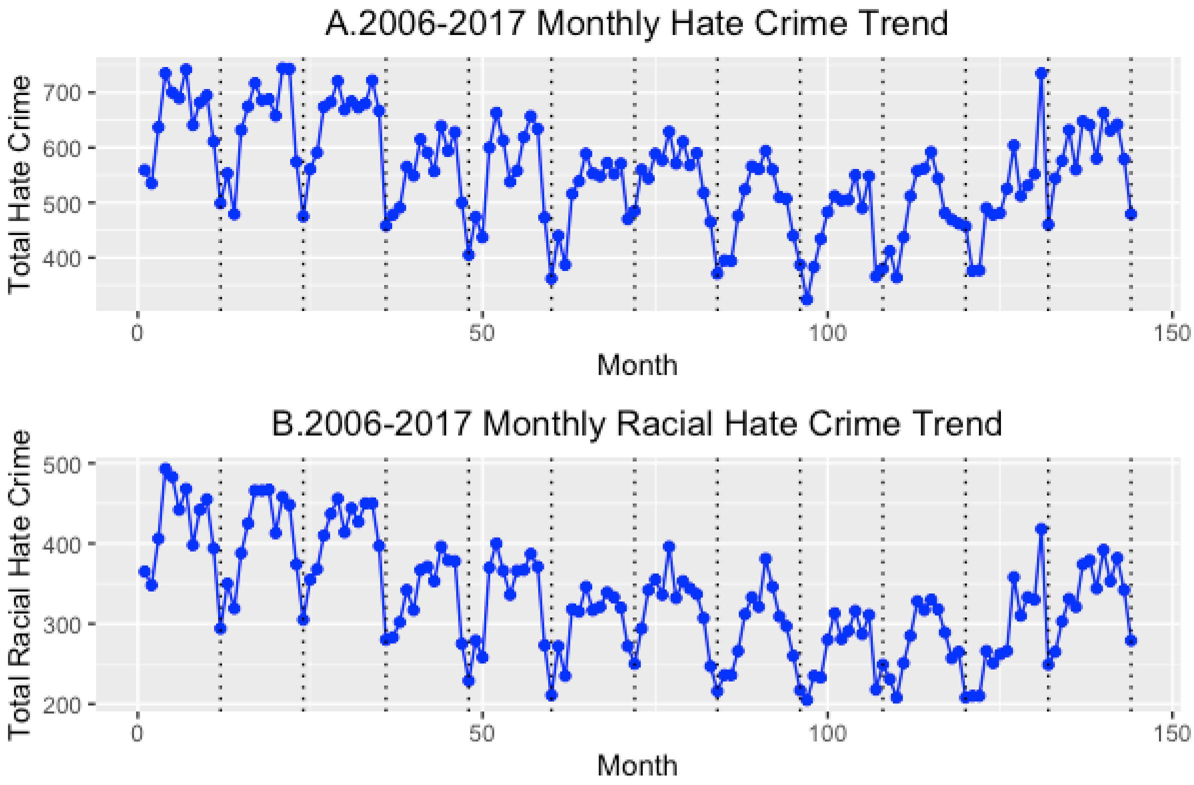

Figure 12: Time Trend of Monthly (Racial) Hate Crime from 2006 to 2017

Notes: Each dash line refers to December of each year.

4.2 Online Political Polarization and Hate Crime

In this section, we illustrate the relationship between hate crime behavior and political polarization by transforming the incident-reporting data into a state-week level data, where each observation represents the number of reported hate crimes in a certain state of a given week.

4.2.1 Regression Results

To illustrate the relationship between ideology and hate crime, we introduced our state-level polarization index proposed in section 3.3.2 to the regression model, and estimate the effect of polarization index on hate crime afterwards. In addition, we also estimate the simultaneous correlation and reverse effect [5] between the two variables, whose results are shown in Appendix A.

Table 1 reports the basic summary statistics of our dependent variables. There are some points to mention in the table. First, a low hate crime rate suggests that hate crime is a rarely happened event in the real world. In addition, there exists about 40% of observations where no hate crime happened.

[5] We estimate the reverse effect by regressing number of hate crime and crime rate on the polarization index next week by weighted least square model.

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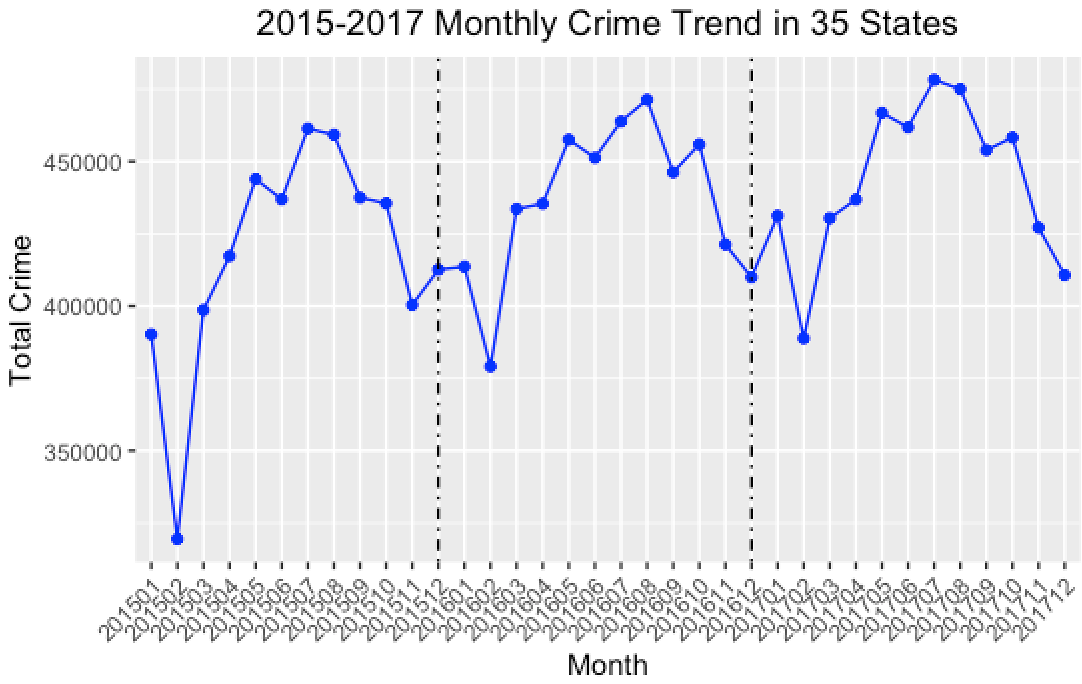

Figure 13: Time Trend of Monthly Crime from 2015 to 2017

Notes: Each dash line refers to December of each year.

We then run the following regression to estimate the effect of polarization level on hate crime afterwards:

$$y_{it} = \beta_1 \cdot polarization_{it-1} + \beta_2 \cdot candidate_{it} + \beta_3 \cdot population_{it} + +state_i + week_t + e_{it} \tag{4.1}$$

where y_{it} is the amount of hate crime or crime rate at state i in week t, $segregation_{it-1}$ represents the state-level polarization index of previous week, and $candidate_{it}$ refers to the candidate gaining more supporters [6].

Since hate crime is a rarely happened event in real world, we use an poisson model to estimate the effect of ideological polarization on hate crime amount. The first panel of Table 2 reports the result of poisson model on hate crime. The result is quite robust among different specification, suggesting that while the polarization index increase in 0.1, there will be 4 more hate crimes and 6 more racial hate crimes on average.

In addition to the poisson model, we propose a weighted least square weighting on population to estimate the effect on hate crime rate. Panel 1 of Table 3 reports the result of weighted least square on hate crime rate, and panel 2 shows the one on racial crime rate. Unlike the result in poisson

[6] We also try different specifications of control variables, including logarithm of population, and ratio of conservatives.

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Table 1: Summary Statistics of (Racial) Hate Crimes

	Hate Crime	Hate Crime Rate	Racial Crime	Racial Crime Rate
Mean	2.31	0.004	1.31	0.002
Standard Deviation	3.58	0.005	2.10	0.0035
Median	1	0.002	0	0
First Quartile	0	0	0	0
Third Quartile	2	0.006	2	0.0032
Max	28	0.053	16	0.04
Min	0	0	0	0
Proportion of 0	0.396	0.396	0.501	0.501
Observations	3,871	3,871	3,871	3,871

Notes: The crime rate is calculated by (number of hate crime/population) * 10,000.

model, the results show no significance in hate crime rate.

4.2.2 Alternative Samples

The results in section 4.2.1 have shown some positive correlation between ideological polarization and amount of hate crime. However, recall Table 1 shows that there exists a high proportion of observations that no hate crime occurs, suggesting that there may exists some states hate crime rarely occurs regardless of the polarization level. Therefore, we conduct several selection on our samples in order to deal with the potential heterogeneity problem.

Table 4 shows the summary statistics of state level hate crime mean and hate crime rate. The medians of the two distribution are 1 and 0.0033, implying that there are less than 1 hate crime per week on average and a crime rate lower than 0.0033 in half of the states.

Based on the mean of hate crime and hate crime rate, we exclude the states where hate crime rarely occurs via different principles while ensuring the representativeness of our sample. First, we select the states with a hate crime mean or hate crime rate higher than median as two different alternative samples. Furthermore, we extend the two sample above by including those with a crime mean or crime rate higher than 0.7 and 0.0016 respectively. The summary statistics of the 4 sub-samples are represented in Table 5. As the table shown, the proportion of observations equaling zero decreases in a large amount in all 4 samples [7].

Table 7 and Table 8 shows the estimated effect of poisson model on hate crime in different alternative samples. The results in 4 different samples show a robust positive effect of polarization index on amount of hate crime, and the estimated effect size is larger than the one shown in Table 2.

[7] The states excluded from different samples are shown in Table 6

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Table 2: Poisson Model on Hate Crime

	Hate Crime			
	(a)	(b)	(c)	(d)
Polarization	0.446**	0.428**	0.420*	0.397*
	(0.223)	(0.212)	(0.278)	(0.229)
Candidate	-0.008	-0.006		
	(0.05)	(0.057)		
Ratio of Conservatives			-0.12	-0.14
			(0.59)	(0.57)
Population	0.0000003		0.0000003	
	(0.0000002)		(0.0000002)	
Log Population		2.43		2.47
		(5.91)		(5.88)
cons	-3.18***	-35.9	-3.07**	-39.3
	(1.2)	(91.12)	(1.23)	(90.7)
Observations	3,822	3,822	3,822	3,822

	Racial Hate Crime			
	(e)	(f)	(g)	(h)
Polarization	0.589*	0.593**	0.628*	0.638**
	(0.304)	(0.290)	(0.333)	(0.317)
Candidate	-0.07	-0.066		
	(0.08)	(0.080)		
Ratio of Conservatives			0.154	0.178
			(0.615)	(0.606)
Population	0.0000002		0.0000002	
	(0.0000003)		(0.0000003)	
Log Population		-0.717		-1.00
		(6.87)		(6.90)
cons	-2.76	9.28	-2.95	13.44
	(1.77)	(105.9)	(1.81)	(106.4)
Observations	3,822	3,822	3,822	3,822

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 3: Weighted Least Square Model on Hate Crime Rate

	Hate Crime Rate			
	(a)	(b)	(c)	(d)
Polarization	0.0018	0.0017	0.0016	0.0015
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
Candidate	0.0002	0.0002		
	(0.0003)	(0.0003)		
Ratio of Conservatives			-0.0008	- 0.001
			(0.002)	(0.002)
Population	0.000		0.000	
	(0.0000)		(0.000)	
Log Population		0.010		0.010
		(0.017)		(0.018)
cons	-0.005*	-0.149	-0.004	-0.147
	(0.003)	(0.269)	(0.004)	(0.272)
R-Squared	0.5189	0.5186	0.5189	0.5186
Observations	3,822	3,822	3,822	3,822

	Racial Hate Crime Rate			
	(e)	(f)	(g)	(h)
Polarization	0.0013	0.0013	0.0014	0.0014
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
Candidate	-0.00004	-0.00004		
	(0.0002)	(0.0002)		
Ratio of Conservatives			0.0004	0.0003
			(0.0013)	(0.0013)
Population	0.000		0.000	
	(0.000)		(0.000)	
Log Population		-0.0005		-0.0005
		(0.011)		(0.012)
cons	-0.002	0.008	-0.002	-0.0077
	(0.002)	(0.176)	(0.003)	(0.179)
R-Squared	0.4060	0.4060	0.4061	0.4060
Observations	3,822	3,822	3,822	3,822

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 4: Summary Statistics of State-level Hate Crime

	Hate Crime	Hate Crime Rate	Racial Crime	Racial Crime Rate
Mean	2.31	0.004	1.314	0.0021
Standard Deviation	3.18	0.002	1.699	0.0015
Median	1	0.003	0.683	0.0019
First Quartile	0.418	0.001	0.253	0.0009
Third Quartile	2.822	0.005	1.873	0.0031
Max	16.47	0.011	8.506	0.0057
Min	0.063	0.0002	0.037	0.0001
Observations	49	49	49	49

The result suggests that the effect of polarization level on hate crime is larger in the states with a higher frequency/crime rate.

Table 9 and Table 10 then shows the estimated effect of weighted least square model on hate crime rate in different alternative samples. Unlike the results in Table 3, the results here show a robust positive effect of polarization index on hate crime rate, suggesting that the polarization level increases the hate crime rate in the states with a higher frequency/crime rate [8].

4.2.3 Discussion

The results in the above sections provide some empirical evidence for the positive relationship ideological polarization and hate crime, suggesting that a higher level of online ideological polarization may increase the amount of hate crime (or the hate crime rate in high-frequency states) next week [9]. Moreover, this kind of effect is larger in the states with higher hate crime frequency or crime rate.

The findings above is quite intuitive due to the fact that there is a correlation between online and offline political behavior. To be more precisely, the increase in online ideological polarization not only reflect a polarization among users' preference, but can also induces a higher level of hatred between different political camps. This kind of hatred provides a motivation to attack those holding an opposite political attitude, resulting in an increase in hate crime.

In addition, Table 12 and Table 13 in Appendix A show a simultaneous positive correlation between polarization level and amount of hate crime, suggesting that a higher level of online ideological polarization often comes with a larger amount of hate crime. However, the correlation here isn't as robust as the main result in this section.

[8] We also run the same regression on those excluded from our sample. The results show no significance in neither of them.

[9] Results in Table 15 and Table 16 in Appendix A suggest that a higher frequency of hate crime and hate crime rate doesn't result in a higher level of ideological polarization, making the causal inference here more valid.

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Table 5: Summary Statistics of Different Samples

	Crime Mean > 1		Crime Mean > 0.7	
	Hate Crime	Hate Crime Rate	Hate Crime	Hate Crime Rate
Mean	4.23	0.005	3.65	0.004
Standard Deviation	4.28	0.004	4.12	0.004
Median	3	0.002	2	0.003
First Quartile	1	0.004	1	0.001
Third Quartile	6	0.007	5	0.007
Max	28	0.025	28	0.037
Min	0	0	0	0
Proportion of 0	0.11	0.11	0.18	0.18
Observations	1,896	1,896	2,291	2,291
	Crime Rate > 0.0033		Crime Rate > 0.0016	
	Hate Crime	Hate Crime Rate	Hate Crime	Hate Crime Rate
Mean	3.66	0.005	2.95	0.005
Standard Deviation	4.42	0.005	4.04	0.005
Median	2	0.005	1	0.004
First Quartile	1	0.001	0	0
Third Quartile	5	0.008	4	0.007
Max	28	0.053	28	0.053
Min	0	0	0	0
Proportion of 0	0.24	0.24	0.32	0.32
Observations	1,975	1,975	2,686	2,686

4.3 Limitations

The main limitation of this section is due to the problem of dark figure of hate crime. First, the crimes happening in jurisdiction of agencies not included in the NIBRS program, which accounts for up to 30% of the whole states, will not be reported to FBI. Next, the determining process of hate crime may lead to a potential selection bias based on decision maker's own cognition of hate crime and political preference. Furthermore, the determining process may be affected by political environment and public opinion then, which is possibly correlated with our interested independent variable, leading to an bias of our estimation.

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Table 6: States Excluded from Samples

	Crime Mean < 1	Crime Mean < 0.7	Crime Rate < 0.0033	Crime Rate < 0.0016
	Alabama	Alabama	Alabama	Alabama
	Alaska	Alaska	Alaska	Arkansas
	Arkansas	Arkansas	Arkansas	Florida
	Delaware	Delaware	Florida	Georgia
	Georgia	Idaho	Georgia	Illinois
	Idaho	Iowa	Illinois	Iowa
	Iowa	Louisiana	Indiana	Louisiana
	Louisiana	Maryland	Iowa	Maryland
	Maine	Mississippi	Louisiana	Mississippi
	Maryland	Montana	Maryland	New Mexico
	Mississippi	Nebraska	Mississippi	Pennsylvania
	Montana	New Hampshire	Missouri	South Carolina
	Nebraska	New Mexico	Nebraska	Wisconsin
	New Hampshire	North Dakota	New Hampshire	Wyoming
	New Mexico	Oklahoma	New Mexico	Texas
	North Dakota	Rhode Island	North Carolina	
	Oklahoma	South Dakota	Oklahoma	
	Rhode Island	Vermont	Pennsylvania	
	South Carolina	Wisconsin	Rhode Island	
	South Dakota	Wyoming	Oregon	
	Vermont		Pennsylvania	
	West Virginia		South Carolina	
	Wisconsin		Texas	
	Wyoming		Delaware	
	Nevada			
States	25	20	24	15

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Table 7: Poisson Model on Hate Crime (Selected by Crime Mean)

	Hate Crime Mean > 1			
	(a)	(b)	(c)	(d)
Polarization	0.481**	0.441**	0.497**	0.446**
	(0.211)	(0.198)	(0.229)	(0.202)
Candidate	0.062*	0.063*		
	(0.035)	(0.036)		
Ratio of Conservatives			0.081	0.040
			(0.632)	(0.614)
Population	0.0000003		0.0000003	
	(0.0000002)		(0.0000002)	
Log Population		5.31		5.40
		(5.96)		(5.90)
cons	1.36	-82.47	-1.40	-83.9
	(1.70)	(93.84)	(1.72)	(93.0)
Observations	1,872	1,872	1,872	1,872
	Hate Crime Mean > 0.7			
	(e)	(f)	(g)	(h)
Polarization	0.491**	0.468**	0.481**	0.452*
	(0.206)	(0.194)	(0.230)	(0.209)
Candidate	0.006	0.008		
	(0.051)	(0.053)		
Ratio of Conservatives			-0.041	-0.068
			(0.594)	(0.574)
Population	0.0000003		0.0000003	
	(0.0000002)		(0.0000002)	
Log Population		2.78		2.83
		(6.08)		(6.04)
cons	-1.41	-42.7	-1.36	-43.3
	(1.71)	(95.8)	(1.73)	(95.2)
Observations	2,262	2,262	2,262	2,262

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 8: Poisson Model on Hate Crime (Selected by Crime Rate)

	Hate Crime Rate > 0.0033			
	(a)	(b)	(c)	(d)
Polarization	0.597***	0.577***	0.563**	0.549**
	(0.220)	(0.204)	(0.278)	(0.255)
Candidate	-0.006	-0.003		
	(0.057)	(0.060)		
Ratio of Conservatives			-0.148	-0.119
			(0.648)	(0.621)
Population	0.0000007***		0.0000007***	
	(0.0000002)		(0.0000002)	
Log Population		4.38		4.47
		(6.91)		(6.85)
cons	-3.41**	-67.8	-3.30*	-69.1
	(1.62)	(108.9)	(1.80)	(107.9)
Observations	1,950	1,950	1,950	1,950
	Hate Crime Rate > 0.0016			
	(e)	(f)	(g)	(h)
Polarization	0.445**	0.430*	0.446*	0.434*
	(0.227)	(0.210)	(0.261)	(0.240)
Candidate	-0.017	-0.016		
	(0.062)	(0.065)		
Ratio of Conservatives			0.001	0.012
			(0.644)	(0.620)
Population	0.0000006**		0.0000006**	
	(0.0000002)		(0.0000002)	
Log Population		3.86		3.81
		(7.00)		(6.95)
cons	-2.12***	-53.8	-2.13***	-53.1
	(0.305)	(94.7)	(0.534)	(94.0)
Observations	2,652	2,652	2,652	2,652

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 9: Weighted Least Square Model on Hate Crime Rate (Selected by Crime Mean)

	Hate Crime Mean > 1			
	(a)	(b)	(c)	(d)
Polarization	0.0024**	0.0024*	0.0026*	0.0024*
	(0.0011)	(0.0012)	(0.0013)	(0.0014)
Candidate	0.0004**	0.0005**		
	(0.0002)	(0.0002)		
Ratio of Conservatives			0.0006	0.0004
			(0.003)	(0.003)
Population	0.000		0.000	
	(0.000)		(0.000)	
Log Population		0.021		0.022
		(0.019)		(0.020)
cons	-0.004	-0.323	-0.004	-0.336
	(0.005)	(0.306)	(0.006)	(0.313)
R-Squared	0.5798	0.5796	0.5796	0.5794
Observations	1,872	1,872	1,872	1,872
	Hate Crime Mean > 0.7			
	(e)	(f)	(g)	(h)
Polarization	0.0024**	0.0022*	0.0024*	0.0021
	(0.0011)	(0.0012)	(0.0013)	(0.0013)
Candidate	0.0002	0.0002		
	(0.0003)	(0.0003)		
Ratio of Conservatives			0.00008	-0.0003
			(0.003)	(0.003)
Population	0.000		0.000	
	(0.000)		(0.000)	
Log Population		0.014		0.014
		(0.019)		(0.019)
cons	-0.004	-0.218	-0.004	-0.222
	(0.004)	(0.298)	(0.005)	(0.302)
R-Squared	0.5612	0.5607	0.5612	0.5607
Observations	2,262	2,262	2,262	2,262

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 10: Weighted Least Square Model on Hate Crime Rate (Selected by Crime Rate)

	Hate Crime Rate > 0.0033			
	(a)	(b)	(c)	(d)
Polarization	0.0038**	0.0037**	0.0037**	0.0037**
	(0.0014)	(0.0014)	(0.0017)	(0.0016)
Candidate	0.0001	0.0001		
	(0.0004)	(0.0005)		
Ratio of Conservatives			-0.0001	-0.0001
			(0.003)	(0.003)
Population	0.000**		0.000**	
	(0.000)		(0.000)	
Log Population		0.022		0.023
		(0.038)		(0.038)
cons	-0.19**	-0.345	-0.019*	-0.352
	(0.009)	(0.605)	(0.010)	(0.594)
R-Squared	0.3440	0.3424	0.3440	0.3424
Observations	1,950	1,950	1,950	1,950
	Hate Crime Rate > 0.0016			
	(e)	(f)	(g)	(h)
Polarization	0.0026*	0.0025*	0.0026	0.0025*
	(0.0014)	(0.0013)	(0.0015)	(0.0015)
Candidate	0.00005	0.00005		
	(0.0004)	(0.0004)		
Ratio of Conservatives			-0.0001	-0.0002
			(0.003)	(0.003)
Population	0.000**		0.000**	
	(0.000)		(0.000)	
Log Population		0.019		0.019
		(0.037)		(0.036)
cons	0.00003	-0.251	0.0001	-0.253
	(0.0016)	(0.498)	(0.003)	(0.492)
R-Squared	0.3580	0.3570	0.3580	0.3570
Observations	2,652	2,652	2,652	2,652

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Chapter 5

Agenda Setting and Public Opinion on Social Media

In this chapter, we identified the posts related to immigration and racial issues, and explore the public opinion on Facebook toward immigrants and blacks. Our analysis results include the supply and demand side of information, and further discuss Trump's impact on agenda setting and public opinion on Facebook.

5.1 Identification of Issue-Related Posts

The task of identifying issue-related posts is dealt as a text classification problem. In this section, we briefly introduce our methodology of the post-selecting process, including data pre-processing process and model selection.

5.1.1 Data Pre-processing

In preparation of building a supervised classification model, we first used a combination of keywords to extract potential related posts as our testing data [1]. Restricting our posts on those containing the keywords ensures a sufficient proportion of posts relating to our interested issues, and further avoids the problem of imbalance data.

We then randomly selected 500 posts each month for each issue to be labeled from the testing data. The selecting process ensures our training data to cover different topics popularly discussed

[1] The keywords used for immigration issues are immigrant, immigration, Muslim, Mexican; The one used for racial issues are African-American and black.

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in each month, making it representative. The posts in training data were labeled in the following criterion artificially: Related topics, the relation with Trump, and sentiments toward targeted group [2].

5.1.2 Classification Model

Model selection has always been a crucial part in classification problem. Traditional statistical learning model such as logistic regression and support vector machine can extract the similarity between texts by comparing the frequency of words or their relationship in each texts. However, a deep learning model able to extract implicit features lying in corpus can do more than that. The one used in this paper, which is also a commonly used text classification model, is the convolutional neural network model. The convolutional layer and max-pooling process in this model learns the meaningful parts correlated with the label within the text during the training process, and uses them as features in classification. The point is that those implicit features extracted in the model are often difficult to identified artificially beforehand, providing the model an advantage on classification of unstrutural data such as texts and images.

In this section, we follow the model suggested by Kim (2014). Figure 14 shows the structure of the model. In the model, we used a pre-trained word2vec on the testing data selected previously as our embedding layer. We then select the most important 20,000 words determined by word frequency as our feature. We use the model to identify not only the related posts but also the sentiment. The validation accuracy is about 80% to 90% at classification part, and 60% to 70% at sentiment analysis.

[2] For example, a post expressing the support of Trump's Muslim ban policy will be labeled as a Muslim, immigration and Trump-related post with a negative sentiment.

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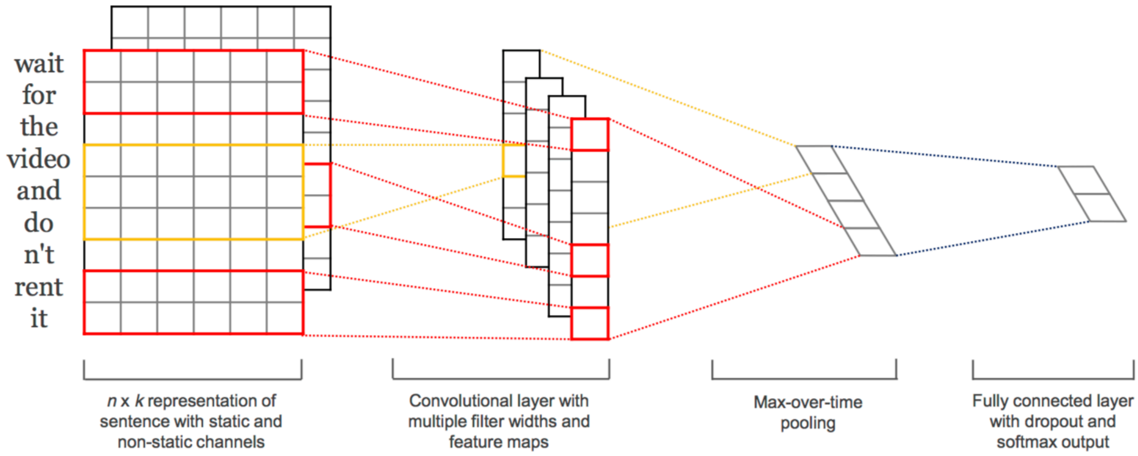

Figure 14: Model Structure of CNN Text Classifier

Notes: By Kim (2014)

5.2 Analysis

This section shows the analysis results of public opinion on Facebook in different dimensions: Media Volume, pages, likes and comments.

5.2.1 Media Volume

Figure 15 and Figure 16 reports the media volume of immigration and race related issues during the campaign. In the figure, there are spikes along with each events [3], suggesting that the amount of posts related to the two issues did increase largely while Trump gave a related controversial speech. In fact, Trump also triggered the discussion on related issues, since Figure 17 and Figure 18 both suggest that the media volume of related issues not mentioning Trump also increases. In addition, Figure 19 shows that Trump's controversial statements was able to attract medias' attention, and often brought him larger media volume on Facebook. This provides some evidence to Trump's impact on media volume.

[3] The events are shown in Table 11

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Table 11: Trump-Related Events

Date	Event
	Immigration
2015-06-16	Trump’s announcement of Candidacy, referring to Mexicans as rapists and criminals.
2015-12-08	Trump proposing his Muslim ban.
2016-08-31	Trump’s immigration speech after meeting with Mexico president.
	Race
2015-06-23	Trump saying that ”African-American youth have no spirit”.
2015-11	Trump tweets false statistics about the percentage of whites killed by blacks.
2016-07-12	Trump tells FOX News that blacks are not necessarily wrong about police mistreatment.
2016-09-20	Trump says that ”African-American communities are in ”the worst shape ever”.
	Randal Pinkett, the first-African American champion of the Apprentice, claims racist comment.

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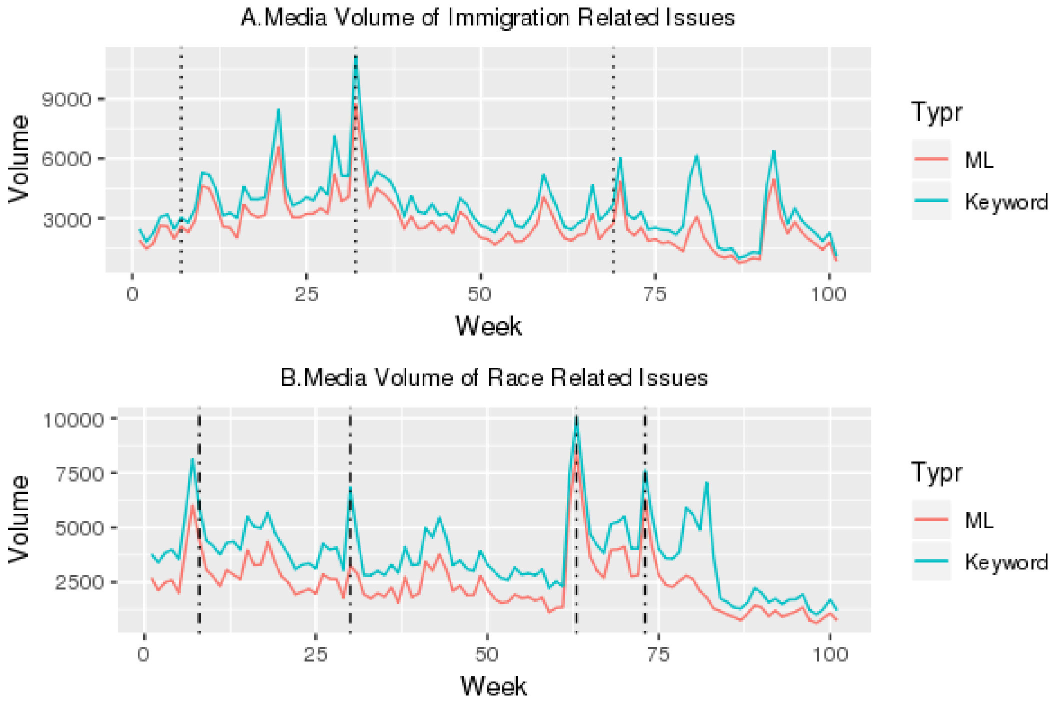

Figure 15: Media Volume of Different Issues

Notes: Each dash line refers to an Trump-related event. The blue line presents the amount of posts selected by keyword combination, and the red one presents the one selected by our model. The two are mainly parallel.

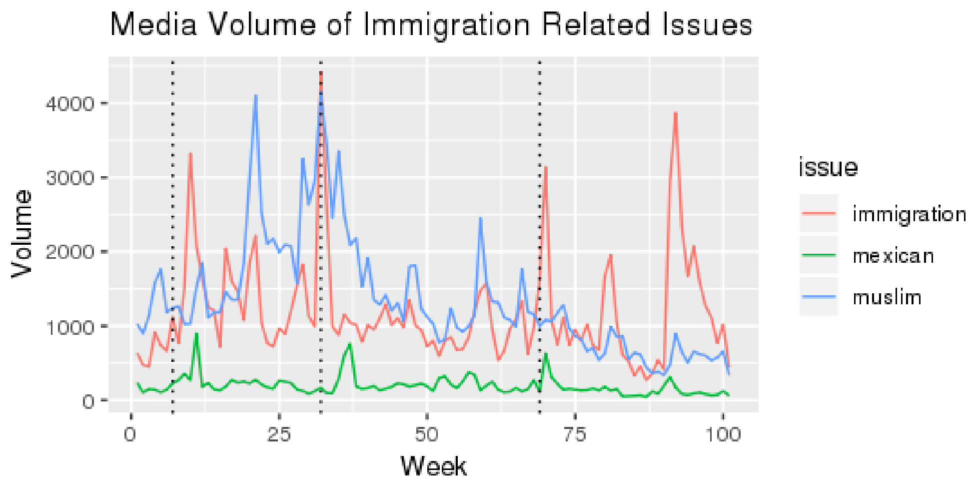

Figure 16: Media Volume of Immigration on Different Topics

Notes: The first and third dash line presents Trump's statement against illegal immigrants and Mexicans, whereas the second one refers to the Muslim ban. The spikes in each issues kind of corresponds to these events.

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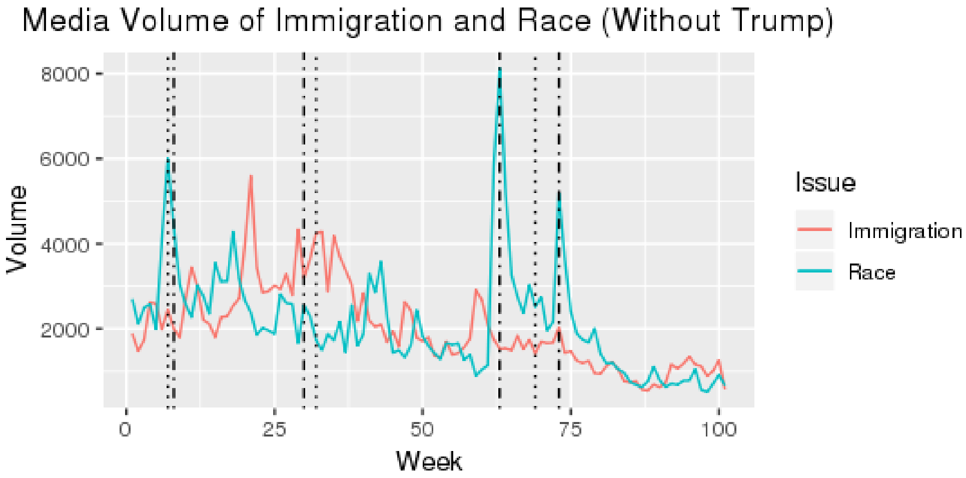

Figure 17: Media Volume of Different Issues Excluded Trump-Related Ones

Notes: The thinner dash line refers to an immigration-related event, whereas the thicker line presents a racial one.

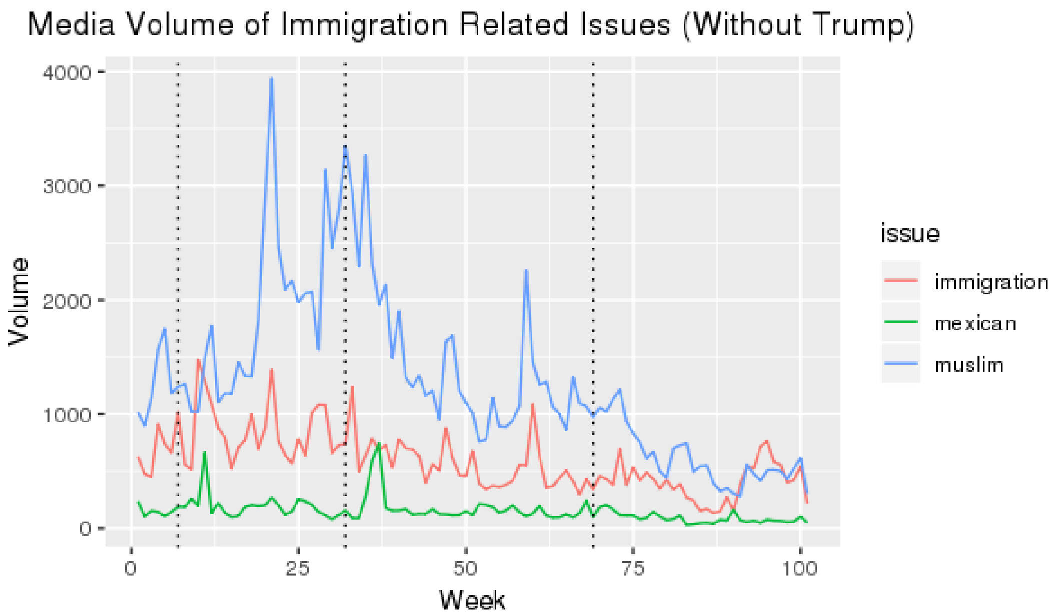

Figure 18: Media Volume of Immigration Excluded Trump-Related Ones

Notes: The first and third dash line presents Trump's statement against illegal immigrants and Mexicans, whereas the second one refers to the Muslim ban. The spikes in each issues kind of corresponds to these events.

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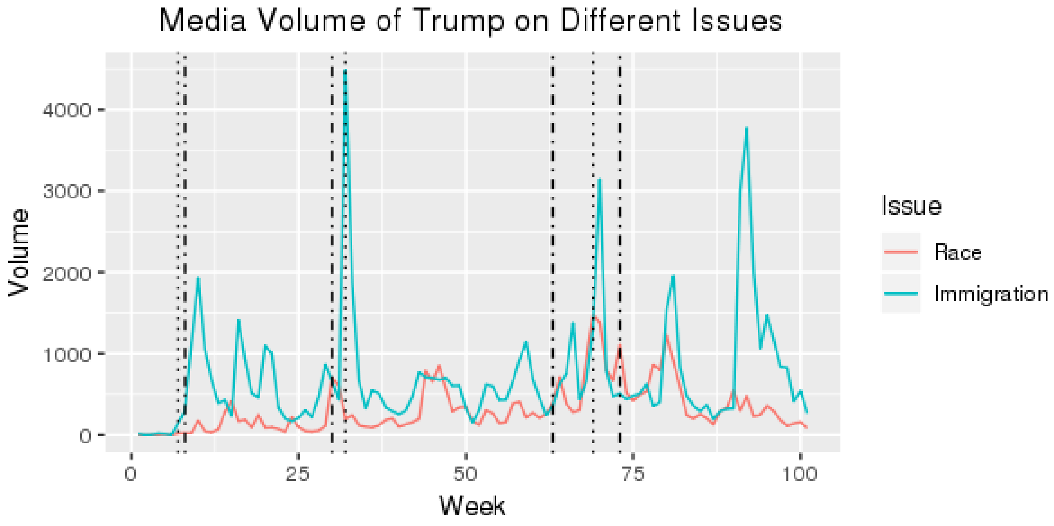

Figure 19: Media Volume of Trump

Notes: The thinner dash line refers to an immigration-related event, whereas the thicker line presents a racial one.

However, Figure 20 suggests that Trump's speeches didn't shape medias' attitude more negative toward immigrants and blacks. Moreover, the overall attitude toward immigrants and blacks tends to become more friendly during the campaign.

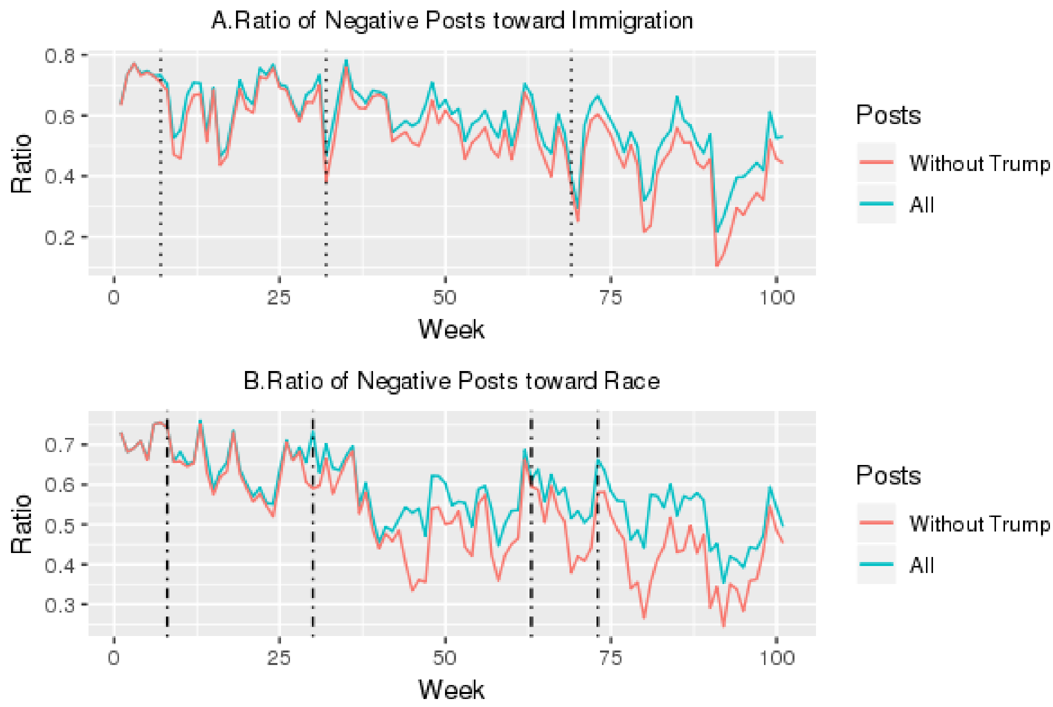

Figure 20: Ratio of Negative Posts toward Race and Immigration Issues

Notes: Each dash line refers to an Trump-related event.

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5.2.2 Supply Side of Information: Pages

We then focus on the supply side of information, which is the pages providing issue-related posts. Figure 21 and Figure 22 present an increase in the amount of pages providing related posts during most of the events. It suggests that Trump's speeches induced a broader media coverage of immigration and race-related issues.

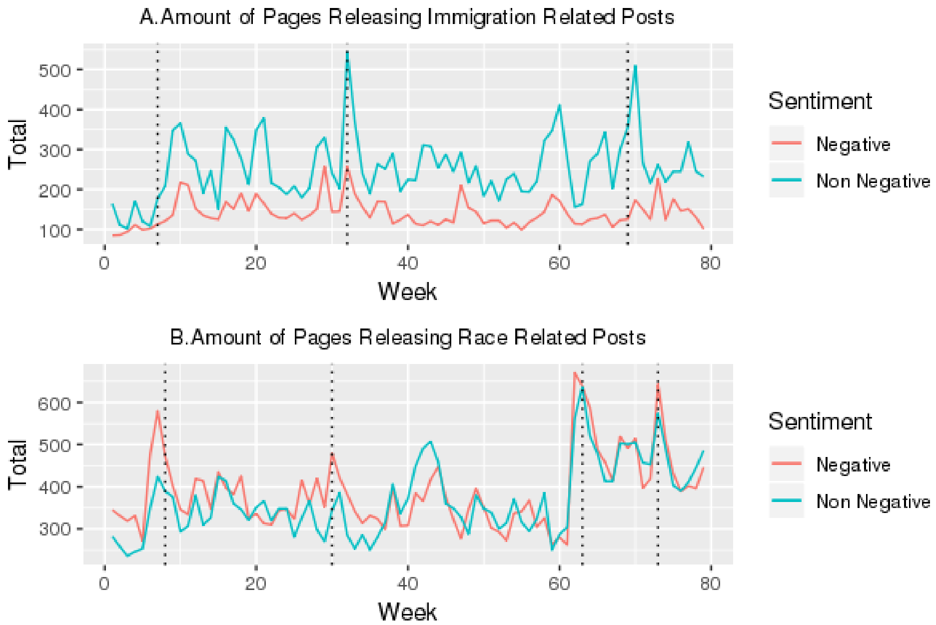

Figure 21: Amount of Pages Providing Related Posts

Notes: Each dash line refers to an Trump-related event.

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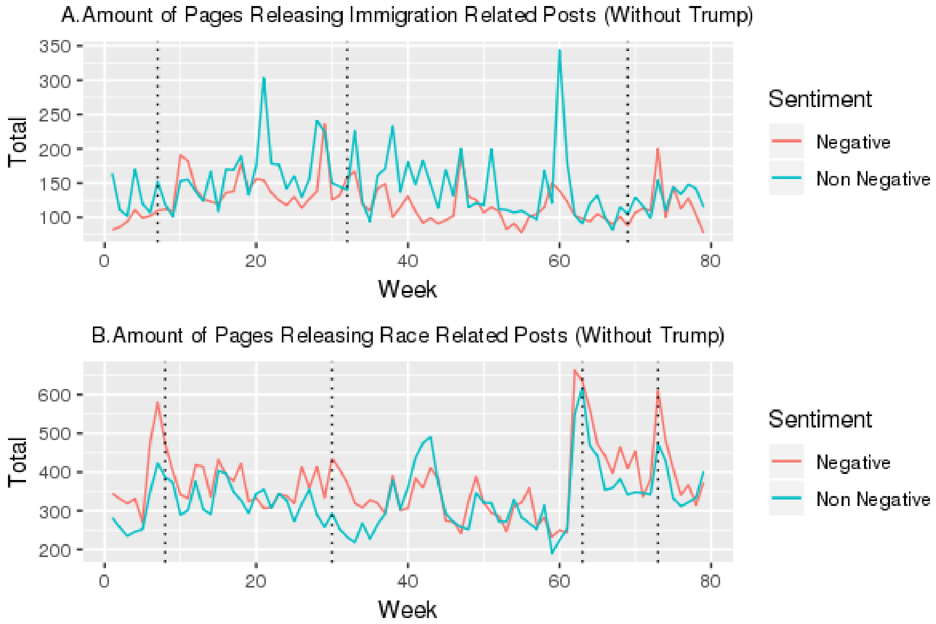

Figure 22: Amount of Pages Releasing Related Posts Excluded Trump-Related Ones

Notes: Each dash line refers to an Trump-related event.

Furthermore, we dig into the ideological composition of these pages. Figure 23 and Figure 24 reports the ratio of conservative pages releasing related posts. There are some interesting patterns to be discussed here. First, the proportion of conservative pages supplying negative posts toward immigrants and blacks are higher than the non negative ones. It implies that comparing to liberals, conservative pages are more willing to release negative posts than non negative ones. Moreover, Trump's speeches toward illegal immigrants and Mexicans increases the ratio of conservatives releasing negative posts, suggesting that Trump has a larger impact on the attitude of those pages similar to him on immigration issues. The results here suggest some impact of Trump on the supply side of information on social media.

In addition, we can also find that comparing to racial issues, the difference of ideological composition between posts with different attitude are larger in immigration. Moreover, the difference of information-supplying behavior between conservatives and liberals are also larger when it comes to immigration issues. This suggests that the polarization level of medias' attitude toward immigration issues is larger than the one on race.

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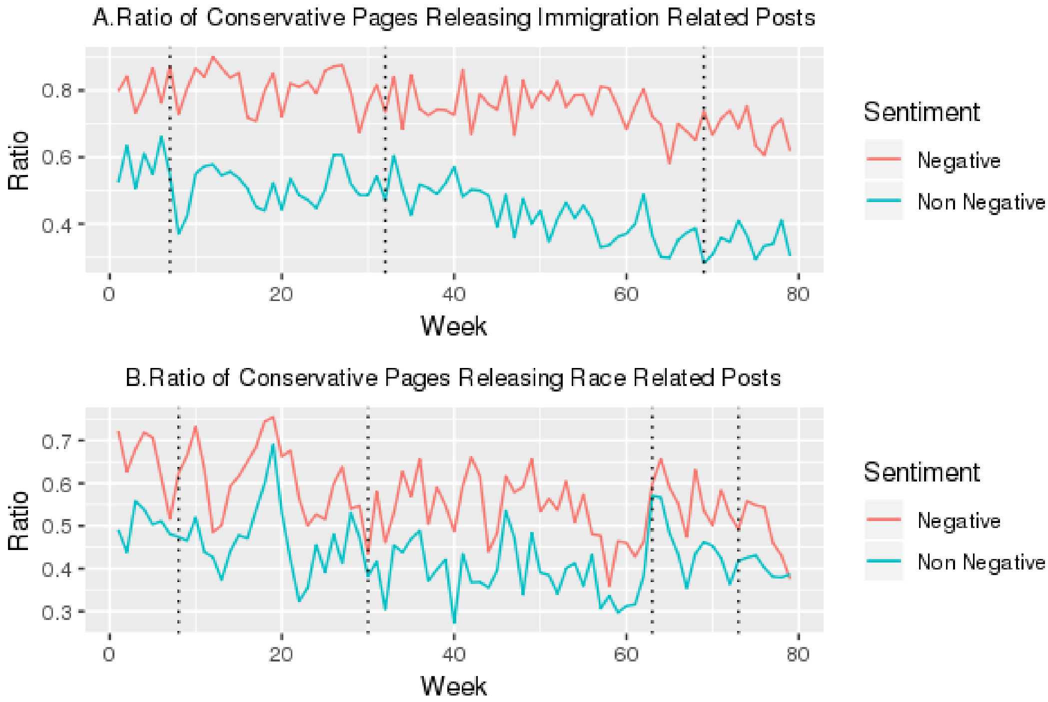

Figure 23: Ideological Composition of Pages Releasing Related Posts

Notes: Each dash line refers to an Trump-related event.

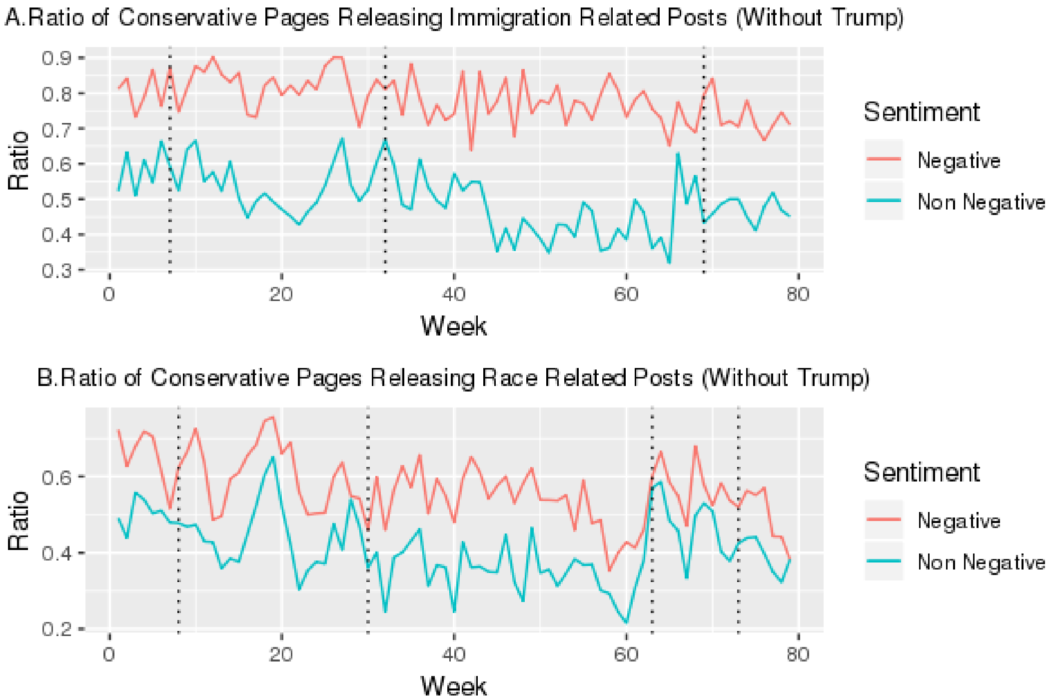

Figure 24: Ideological Composition of Pages Releasing Related Posts Excluded Trump

Notes: Each dash line refers to an Trump-related event.

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5.2.3 Demand Side of Information: Users' Likes

We then turn to the demand side of online information by exploring the time trend of users' liking behavior on interested issues. Figure 25 and Figure 26 shows the amount of likes on related posts and the amount of users attracted by these issues respectively. However, there appears to be no spikes in neither amount of likes or attracted users during the events, even though the media coverage and volume both increased. The analysis results show no evidence that Trump's speeches induce a larger demand in immigration and race-related information.

Figure 25: Amount of Likes on Related Posts

Notes: Each dash line refers to an Trump-related event.

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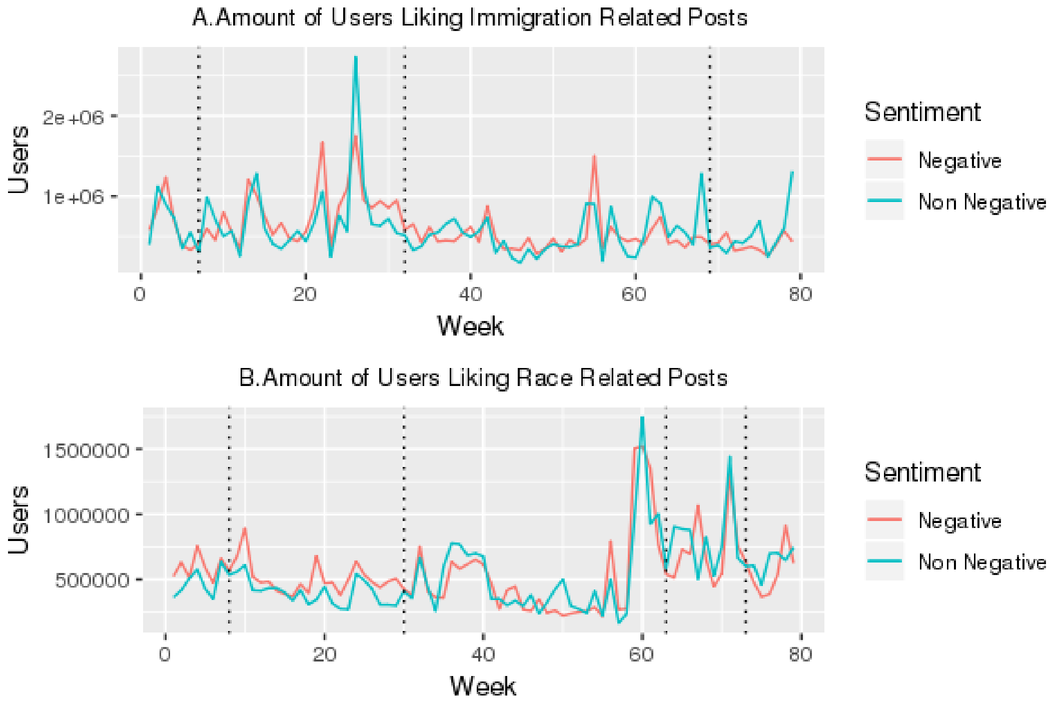

Figure 26: Amount of Users Liking Related Posts

Notes: Each dash line refers to an Trump-related event.

We then explore the ideological composition of the users consuming issue-related information. Figure 27 presents the ratio of conservatives. doesn't increase obviously during each event. The results show a little spike in race-related issue at week 8 and week 73, when Trump commented on African-American youth and communities. In addition, the figure also suggests that conservative users are more active on negative posts than liberal user on immigration. However, this kind of difference isn't that obvious when it comes to racial issue. In addition, the difference of ideological composition between negative and non negative posts are also larger on immigration issues. Recall in section 5.2.2 that the polarization level on immigration issues is larger than race on supply side, the demand side shows a similar tendency here [4].

[4] The ideological polarization on immigration and race-related posts are shown in appendix B.1

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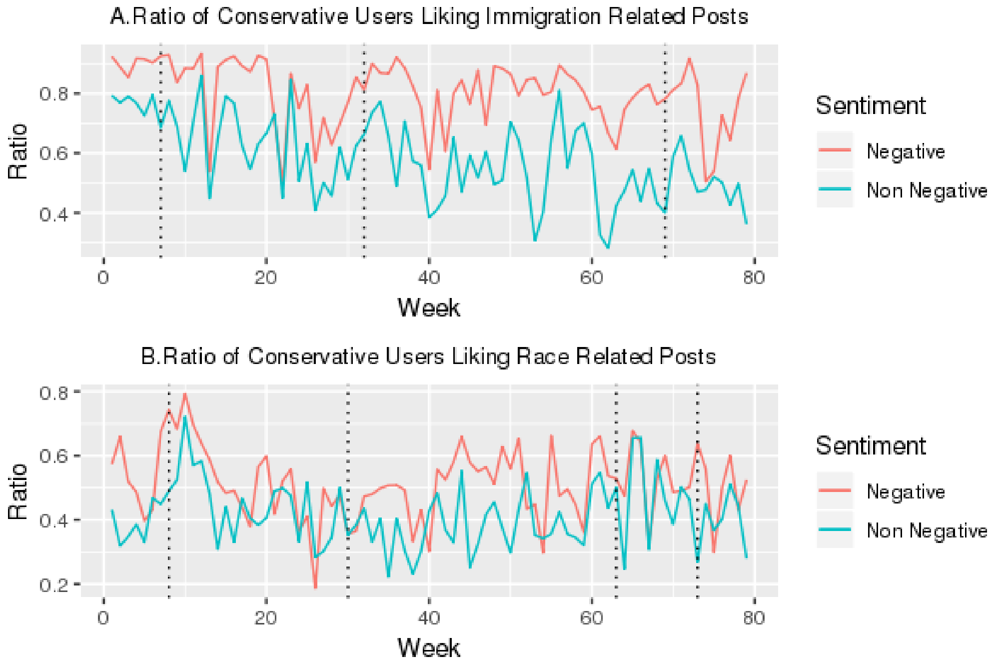

Figure 27: Ideological Composition of Users Liking Related Posts

Notes: The ratio of conservatives within all users are approximately 40%.

We are also interested in the users attracted by issue-related posts with extreme ideology score. Figure 28 shows the proportion of extreme users [5] attracted by negative information, suggesting that comparing to far-left politics, the negative posts were more attractive to the far-right ones, consistent with the attitude of the two parties. The time series of proportion of far-right politics liking posts with different attitude in Figure 29 further shows that information negative to immigrants and blacks were more attractive to users on an far-right position on ideological spectrum than the non negative ones. In addition, the consumer of information related to both issues tended to become more extreme during the campaign. However, it seems that Trump has no obvious influence on the liking behavior of extremest.

[5] We define users with an absolute value of ideology score larger than 1 as extreme users here. The result of the other definition, which is users with an ideology score out of 2 standard deviations, are shown in Appendix B.2.

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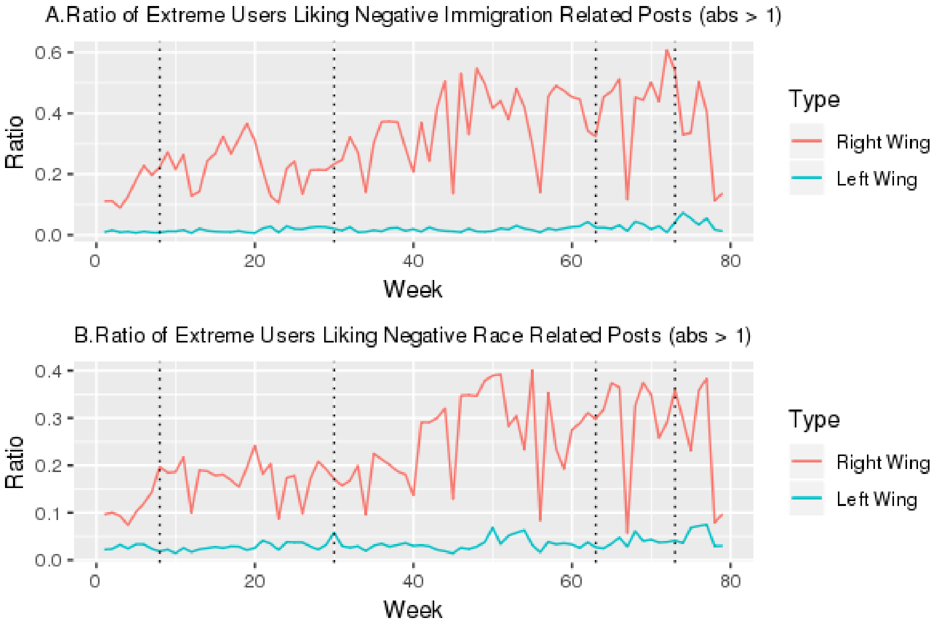

Figure 28: Ratio of Extreme Users Liking Related Posts

Notes: Each dash line refers to an Trump-related event.

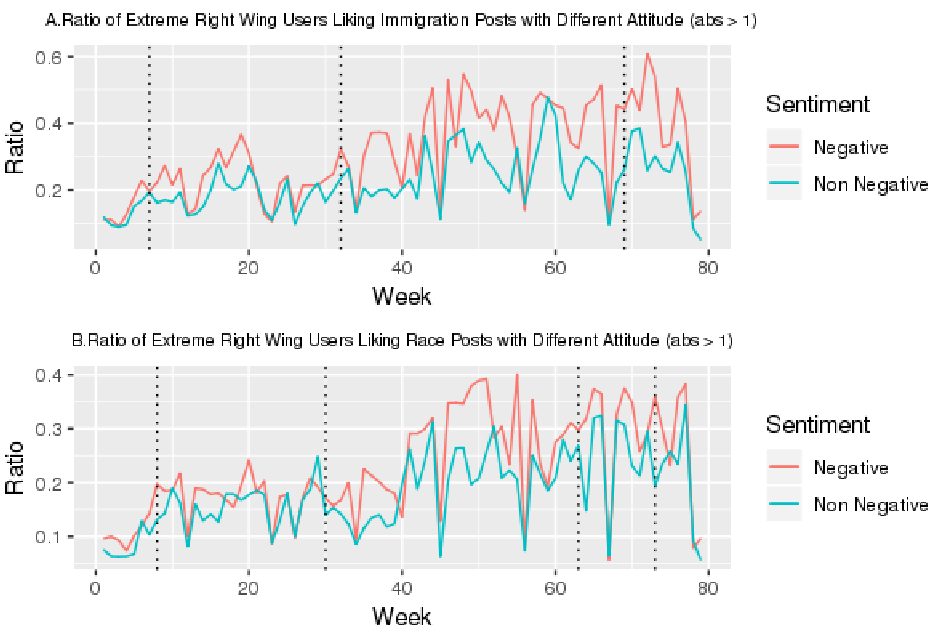

Figure 29: Ratio of Far-Right Politics Liking Related Posts

Notes: Each dash line refers to an Trump-related event.

5.2.4 Demand Side of Information: Presidential Candidates' Followers

Besides the liking behavior of all users on Facebook, we are also curious about the information preference of those newly attracted by presidential candidates each week. Figure 30 and Figure 31

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shows the proportion of Trump and Clinton's followers consuming issue-related information respectively [6]. The figures suggest that comparing to Clinton, Trump's followers prefer information negative to immigrants and blacks more. However, there are no evidence suggesting that Trump's followers pay more attention on immigration and racial issues than Clinton's.

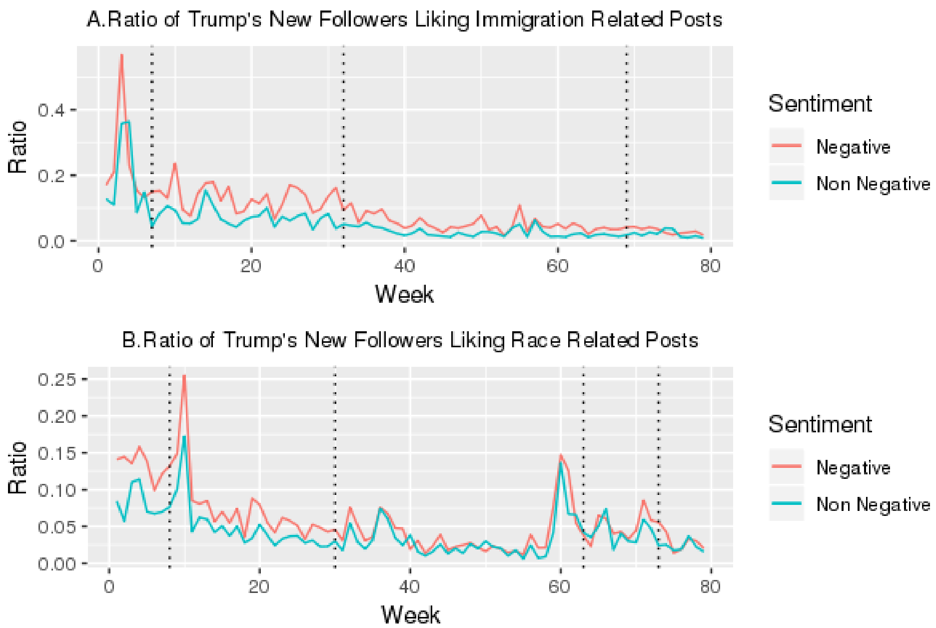

Figure 30: Ratio of Trump's Followers Liking Issue-Related Posts (Without Trump)

Notes: Each dash line refers to an Trump-related event.

[6] We consider the posts not related to Trump only to observe the true preference of Trump's followers on related information.

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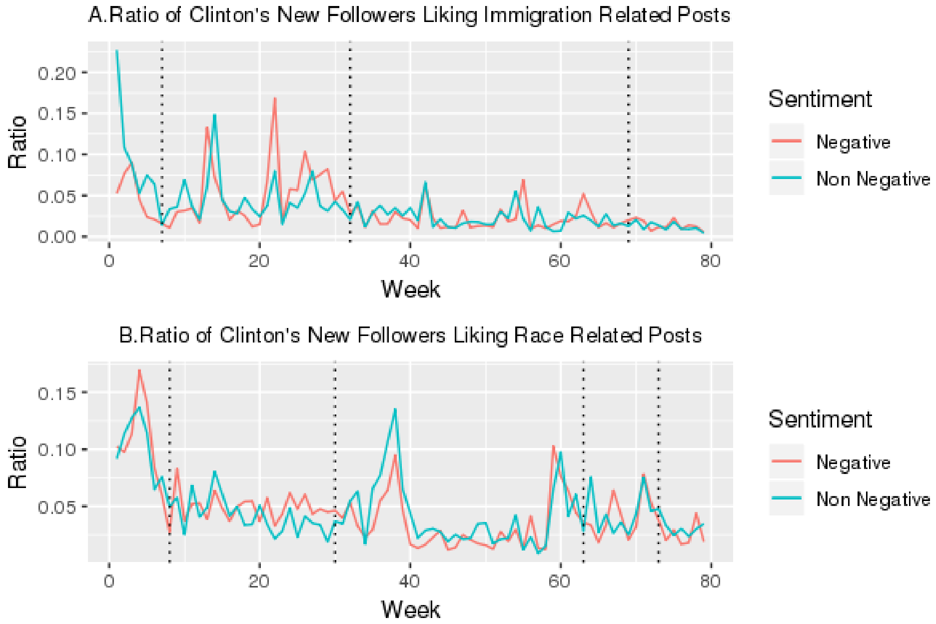

Figure 31: Ratio of Clinton's Followers Liking Issue-Related Posts (Without Trump)

Notes: Each dash line refers to an Trump-related event.

5.2.5 Demand Side of Information: Users' Comments

Different from the section above, we focus on users commenting on posts related to our interested issues. Figure 32 shows the amount of comments on related posts. Similar with the results in section 5.2.3, the amount of comments didn't increase even though the media coverage and volume both increased. Figure 33 further shows the time trend of comments per posts on average, showing no evidence that Trump's speeches induced a broader discussion on related issues among users.

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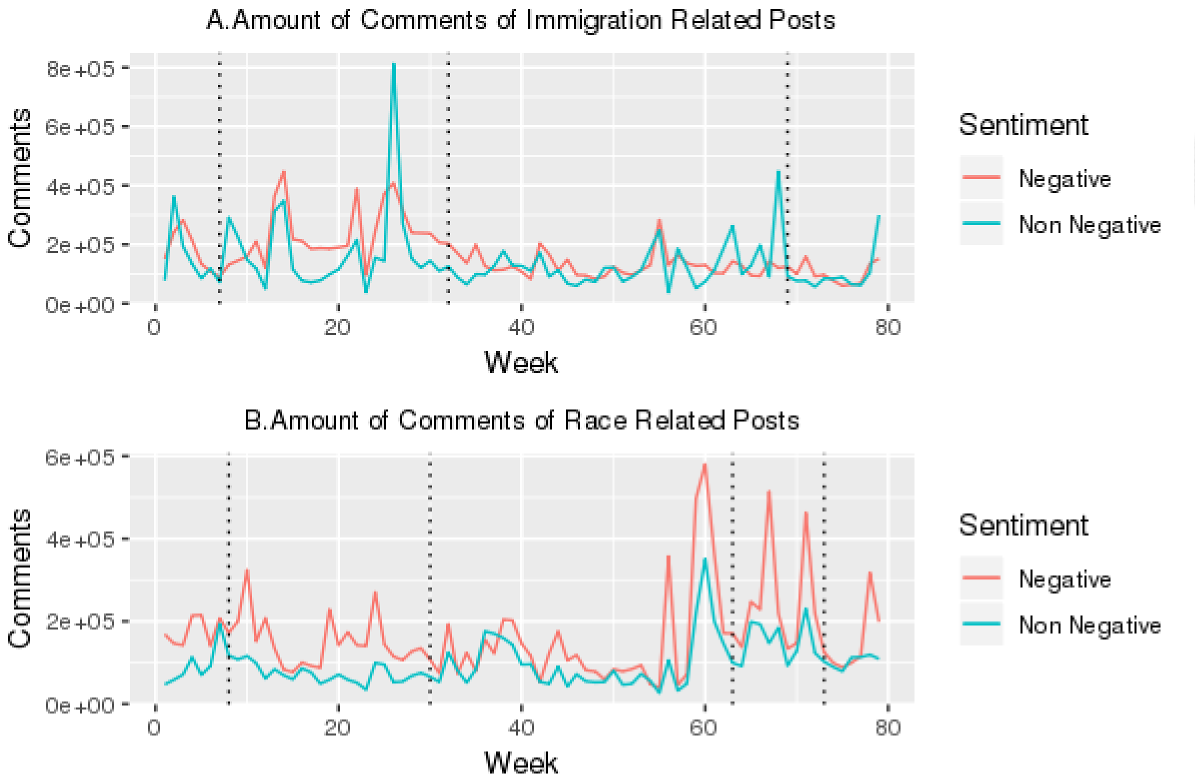

Figure 32: Amount of Comments on Related Posts

Notes: Each dash line refers to an Trump-related event.

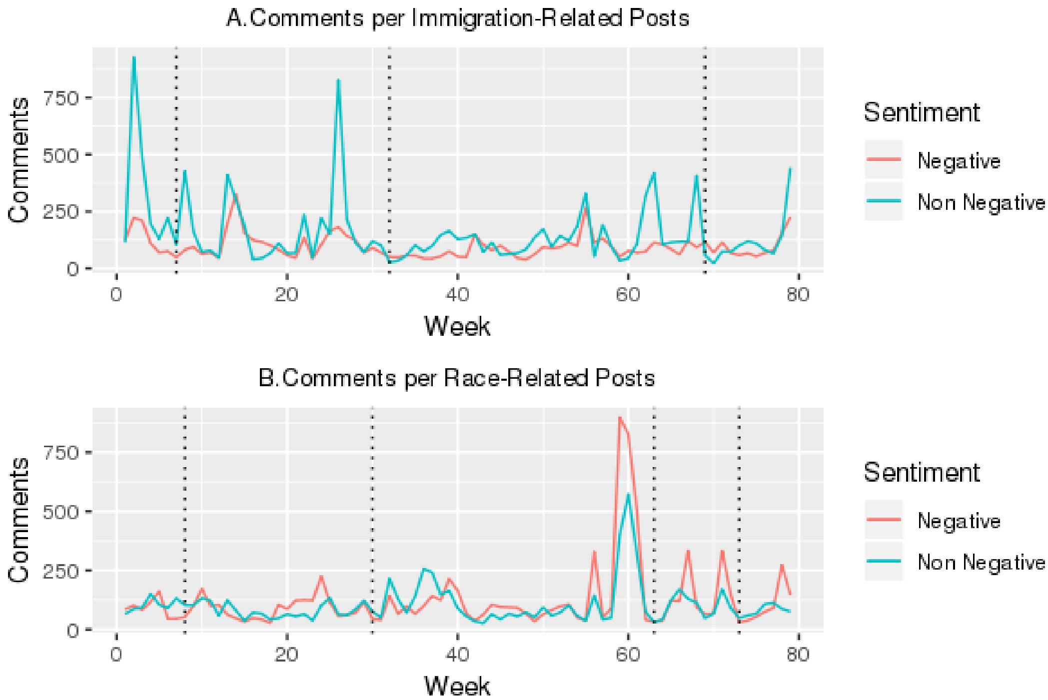

Figure 33: Comment per Posts on Related Issues

Notes: Each dash line refers to an Trump-related event.

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For the ideological composition of the users commenting on related posts, Figure 34 shows that there are no huge increase in the proportion of conservatives during the events. Similar to the results in users' liking reaction, conservative users are more active on negative posts than liberals on immigration-related posts, and this kind of difference isn't that when it comes to racial ones. The difference of ideological composition between negative and non negative posts are also larger on immigration issues. The results suggest that comparing to race-related issues, the discussion on Facebook tends to be more polarized toward immigrants.

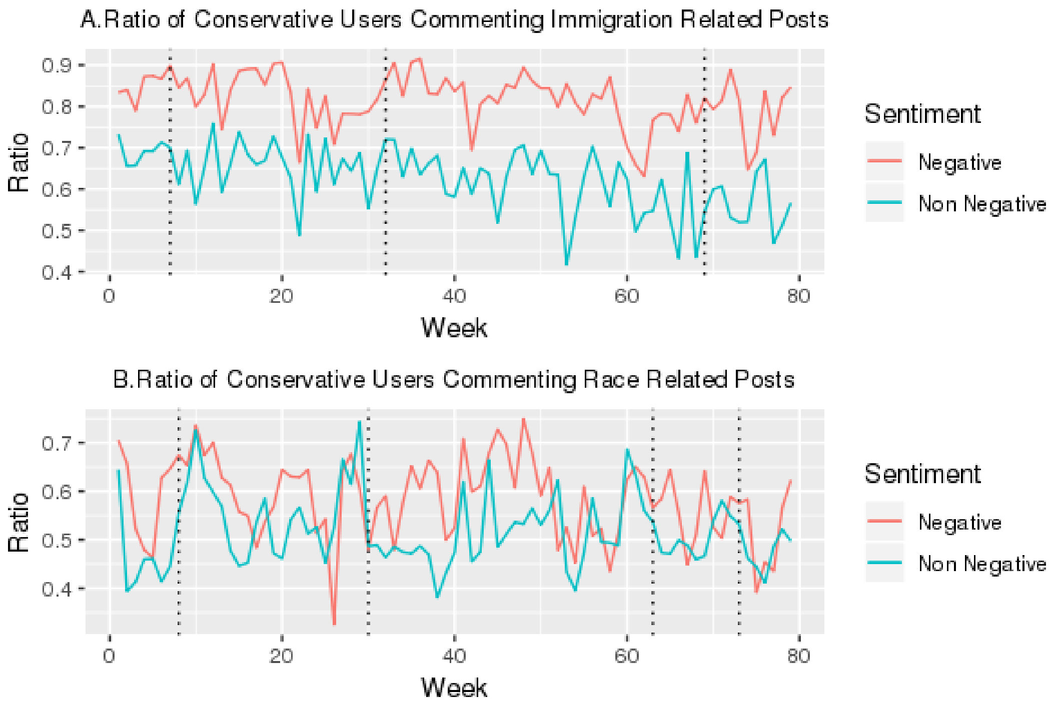

Figure 34: Ideological Composition of Users Commenting on Related Posts

Notes: Each dash line refers to an Trump-related event.

The users commenting on issue-related posts with extreme ideology score are also interested in this section. Figure 35 shows the proportion of extreme users [7] commenting on negative issue-related posts. Similar to the one discussed in section 5.2.3, far-right politics were more willing to participate in the discussion under negative information comparing to far-left ones. Besides, the ratio of far-right politics commenting on immigration-related posts increased during the campaign, implying that the discussion on Facebook tends to be more unfriendly toward immigrants since far-right politics are harsh on these issues.

Figure 29 further shows the proportion of far-right politics commenting on posts with different attitude. The figure suggests that far-right politics are more willing to make comments on informa-

[7] We define users with an absolute value of ideology score larger than 1 as extreme users here. The result of the other definition, which is users with an ideology score out of 2 standard deviations, are shown in Appendix B.3.

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tion negative toward immigrants than the non negative ones, while the tendency isn't quite obvious at the racial part. The analysis results also provide no evidence to Trump's impact on commenting behavior of extremest.

Figure 35: Ratio of Extreme Users Commenting Related Posts

Notes: Each dash line refers to an Trump-related event.

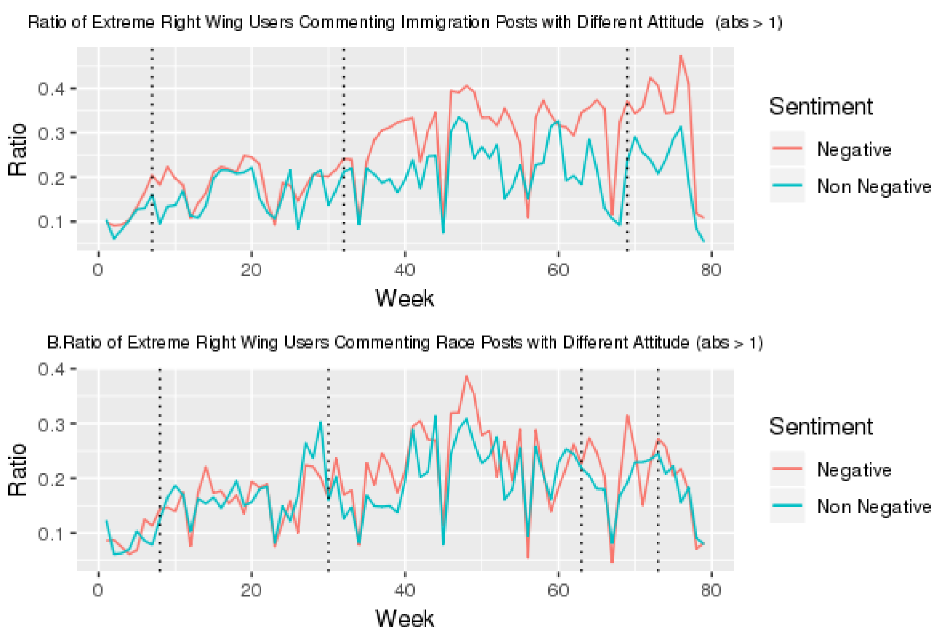

Figure 36: Ratio of Far-Right Politics Commenting Related Posts

Notes: Each dash line refers to an Trump-related event.

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5.2.6 Discussion

The analysis results in this section provide some implication of public opinion toward immigrants and blacks and Trump's impact on agenda setting on social media. First, we find some evidence of Trump inducing medias' awareness toward immigration and racial issues by the increase in media volume and media coverage during the events. However, the change in supply side of information doesn't result in a larger exposure of related information to Facebook users, due to the fact that the users liking related posts didn't increase during Trump's behavior. These results suggest that although Trump was influential on agenda building, there was a lack of first level agenda-setting effect [8].

We also find that there are some difference between information preference of conservatives and liberals on both supply and demand side. Comparing to liberals, conservatives are more interested in those information negative toward immigrants and blacks. Moreover, This kind of polarization are more obvious on immigration issues. However, there are no evidence showing that Trump had a significant impact on and users' behavior and public attitude [9].

The main limitation of this section is the lack of socioeconomic variables of each users, making it difficult to explore the heterogeneity in the impact of Trump and users' demand in information between different demographic groups.

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[8] How media uses objects or issues to influence the people on what they should think about.

[9] We also explore the relationship between public opinion and hate crime, using the index of media volume and negative volume. However, the results show no significance.

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Chapter 6

Conclusion

In this paper, we conduct several exploratory analysis on Facebook data containing a large amount of posts and user reaction relating to 2016 presidential election, and provide some implication of the polarization level and public opinion on Facebook. In Chapter 3, we propose an ideological measure of Facebook users and further construct a polarization index. Furthermore, we analyze the ideological polarization among the two presidential candidates' followers, and apply the segregation index proposed by Gentzkow and Shapiro (2011) on their fan pages. The results show an consistently increasing time trend of polarization level in different dimensions on Facebook during the campaign. Recall the finding of Hansen and Kosiara-Pedersen (2017) suggesting that political campaign induces a higher level of political polarization, our findings present a similar conclusion on social media. Additionally, we also find some evidence from our data to the larger impact of Trump on conservatives' political behavior than Clinton on liberals.

We further explore the relationship of hate crime and ideological polarization using data from FBI and a state-level polarization index in Chapter 4. The results suggest that a higher online ideological polarization level increases the amount of hate crime next week, and the effect is larger in the states with higher frequency of hate crime or crime rate. The results here provide some empirical evidence of the impact of online political preference on offline hate crime behavior.

In regard to Trump's impact on agenda setting and public opinion on Facebook, we find some evidence suggesting Trump's impact on agenda building in Chapter 5. To be more precisely, the increase in both media volume and media coverage during Trump's controversial statements suggests an effect of Trump on medias' awareness toward immigration and racial issues. However, the exposure of information related to immigrants and blacks to users doesn't appear to have a similar pattern. In addition, the liking and commenting behavior of conservatives and liberals suggest a difference between the information preference of partisans, though there are no evidence to an

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impact of Trump on public attitude.

There remain some improvements and future work in this paper. First, the segregation level among all politicians' pages is also inspiring when it comes to polarization on social media. Different specifications and identification strategy on hate crime analysis are also required for more robust results as well as causal inference. In addition, there exists an amount of possible future works in exploring public opinion and agenda setting on Facebook using our data. First, how receiving information with different attitude toward immigrants and blacks affects users' political attitude, particularly ideology, along with comments sentiment and the impact of discussion between users with different political preference on users' attitude, remain interesting research questions. Besides, statistical inference on the difference before and after Trump's speeches is in need to identify Trump's impact on public opinion and agenda setting.

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Appendix A

Hate Crime Regression

Table 12: Simultaneous Poisson Model on Hate Crime

	Hate Crime			
	(a)	(b)	(c)	(d)
Polarization	0.368*	0.346*	0.447	0.405*
	(0.215)	(0.201)	(0.278)	(0.245)
Candidate	0.005	0.007		
	(0.065)	(0.067)		
Ratio of Conservatives			0.243	0.18
			(0.611)	(0.59)
Population	0.0000003		0.0000003	
	(0.0000002)		(0.0000002)	
Log Population		2.07		1.99
		(5.91)		(5.81)
cons	-3.02***	-33.4	-3.28**	-32.4
	(1.13)	(91.04)	(1.31)	(89.6)
Observations	3,871	3,871	3,871	3,871

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 13: Simultaneous Poisson Model on Racial Hate Crime

	Racial Hate Crime			
	(e)	(f)	(g)	(h)
Polarization	0.513*	0.513**	0.705*	0.715*
	(0.277)	(0.258)	(0.407)	(0.375)
Candidate	-0.05	-0.046		
	(0.07)	(0.072)		
Ratio of Conservatives			0.617	0.641
			(0.766)	(0.747)
Population	0.0000002		0.0000001	
	(0.0000003)		(0.0000003)	
Log Population		-0.605		-1.24
		(7.03)		(7.02)
cons	-2.68	7.57	-3.35*	16.60
	(1.76)	(108.4)	(2.02)	(108.2)
Observations	3,871	3,871	3,871	3,871

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 14: Simultaneous Weighted Least Square Model on Hate Crime Rate

	Hate Crime Rate			
	(a)	(b)	(c)	(d)
Polarization	0.001	0.001	0.0016	0.0014
	(0.001)	(0.001)	(0.0012)	(0.0012)
Candidate	0.0002	0.0002		
	(0.0004)	(0.0004)		
Ratio of Conservatives			0.0004	0.00003
			(0.002)	(0.002)
Population	0.000		0.000	
	(0.0000)		(0.000)	
Log Population		0.008		0.009
		(0.017)		(0.017)
cons	-0.004*	-0.129	-0.005	-0.134
	(0.002)	(0.265)	(0.004)	(0.268)
R-Squared	0.5184	0.5182	0.5184	0.5181
Observations	3,871	3,871	3,871	3,871

	Racial Hate Crime Rate			
	(e)	(f)	(g)	(h)
Polarization	0.001	0.001	0.0016	0.0015
	(0.0007)	(0.0007)	(0.0010)	(0.0010)
Candidate	0.00001	0.00001		
	(0.0001)	(0.0001)		
Ratio of Conservatives			0.0014	0.0012
			(0.0016)	(0.0016)
Population	0.000		0.000	
	(0.000)		(0.000)	
Log Population		-0.0004		-0.00004
		(0.011)		(0.011)
cons	-0.002	0.007	-0.003	-0.0007
	(0.002)	(0.178)	(0.003)	(0.180)
R-Squared	0.4051	0.4050	0.4052	0.4051
Observations	3,871	3,871	3,871	3,871

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 15: Hate Crime Frequency on Polarization

	Hate Crime			
	(a)	(b)	(c)	(d)
Crime	0.0003	0.0003	-0.0002	-0.0003
	(0.0004)	(0.0005)	(0.0006)	(0.0007)
Candidate	-0.013**	-0.014**		
	(0.006)	(0.006)		
Ratio of Conservatives			-0.802***	-0.788***
			(0.174)	(0.176)
Population	0.000**		0.000***	
	(0.000)		(0.000)	
Log Population		-0.119		-0.333
		(0.779)		(0.848)
cons	1.14***	2.70	1.82***	6.59
	(0.099)	(11.98)	(0.213)	(13.06)
R-Squared	0.9307	0.9302	0.9427	0.9417
Observations	3,822	3,822	3,822	3,822

	Racial Hate Crime			
	(e)	(f)	(g)	(h)
Crime	0.0004	0.0004	0.0002	0.0002
	(0.0007)	(0.0008)	(0.0006)	(0.0007)
Candidate	-0.013**	-0.014**		
	(0.006)	(0.006)		
Ratio of Conservatives			-0.800***	-0.786***
			(0.172)	(0.173)
Population	0.000**		0.000***	
	(0.000)		(0.000)	
Log Population		-0.114		-0.334
		(0.781)		(0.849)
cons	1.14***	2.64	1.82***	6.60
	(0.099)	(12.02)	(0.213)	(13.06)
R-Squared	0.9307	0.9302	0.9427	0.9417
Observations	3,822	3,822	3,822	3,822

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Table 16: Hate Crime Rate on Polarization

	Hate Crime Rate			
	(a)	(b)	(c)	(d)
Crime Rate	0.433	0.390	0.319	0.266
	(0.396)	(0.388)	(0.300)	(0.303)
Candidate	-0.013**	-0.014**		
	(0.006)	(0.006)		
Ratio of Conservatives			-0.800***	-0.785***
			(0.171)	(0.172)
Population	0.000**		0.000***	
	(0.000)		(0.000)	
Log Population		-0.120		-0.338
		(0.778)		(0.846)
cons	1.14***	2.72	1.82***	6.65
	(0.099)	(11.98)	(0.213)	(13.03)
R-Squared	0.9307	0.9302	0.9427	0.9417
Observations	3,822	3,822	3,822	3,822
	Racial Hate Crime Rate			
	(e)	(f)	(g)	(h)
Crime Rate	0.600	0.570	0.538	0.500
	(0.575)	(0.563)	(0.498)	(0.488)
Candidate	-0.013**	-0.014**		
	(0.006)	(0.006)		
Ratio of Conservatives			-0.800***	-0.786***
			(0.171)	(0.172)
Population	0.000**		0.000***	
	(0.000)		(0.000)	
Log Population		-0.117		-0.335
		(0.779)		(0.847)
cons	1.14***	2.67	1.82***	6.62
	(0.099)	(11.99)	(0.213)	(13.03)
R-Squared	0.9307	0.9302	0.9427	0.9417
Observations	3,822	3,822	3,822	3,822

Notes: p-value: * < 0.1, ** < 0.05, *** < 0.01. The standard errors are robust and clustered by states.

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Appendix B

B.1 Ideological Polarization on Immigration/Race Related Posts

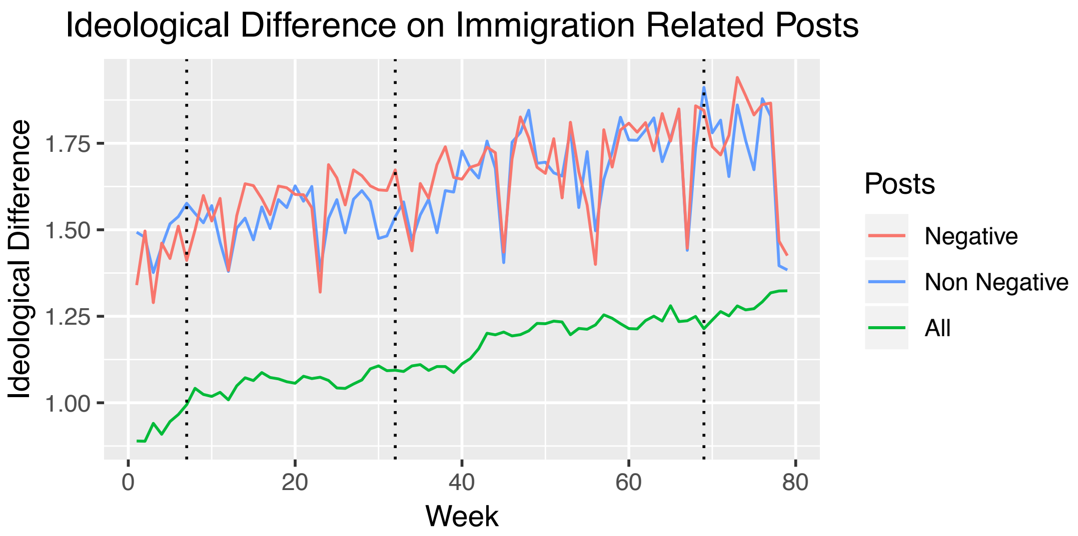

Figure 37: Ideological Polarization on Immigration Related Posts

Notes: The figure shows and overall increasing time trend in ideological polarization. Moreover, the level of polarization among users liking immigration issues are higher than the platform.

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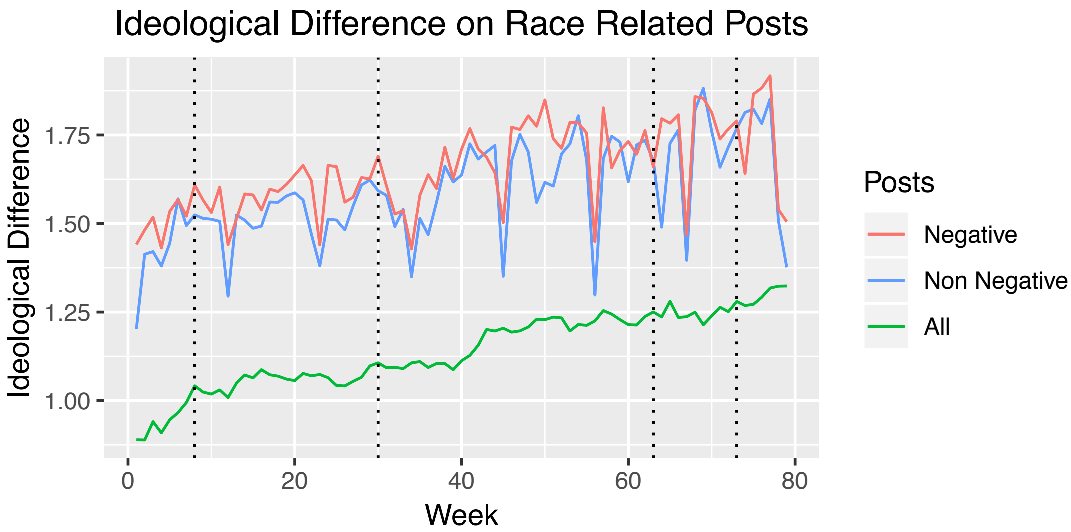

Figure 38: Ideological Polarization on Race Related Posts

Notes: The figure shows and overall increasing time trend in ideological polarization. Moreover, the level of polarization among users liking racial issues are higher than the platform.

B.2 Extreme Users Liking Immigration/Race Related Posts

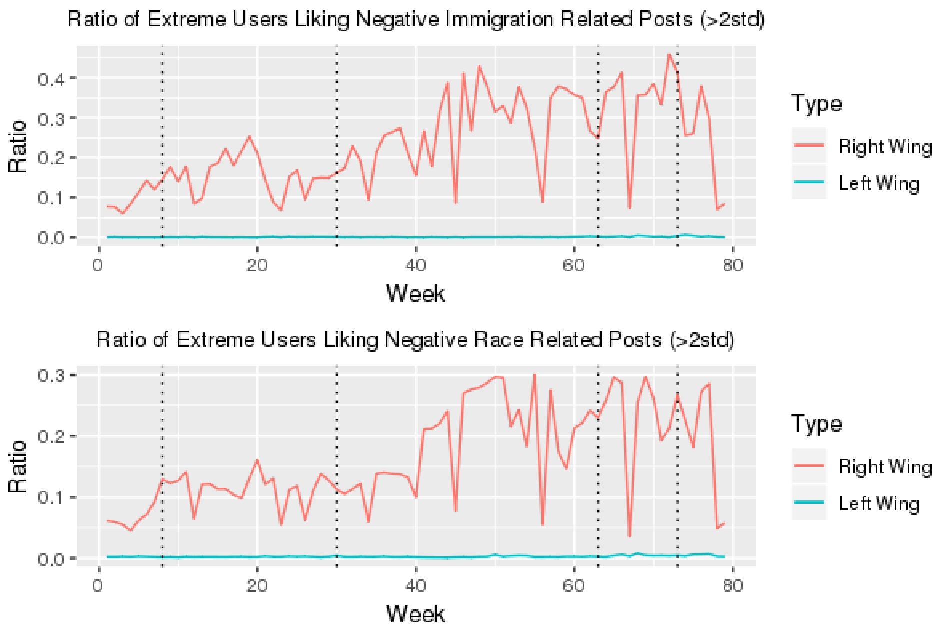

Figure 39: Ratio of Extreme Users Liking Related Posts

Notes: The time series here is basically same as the absolute value measure.

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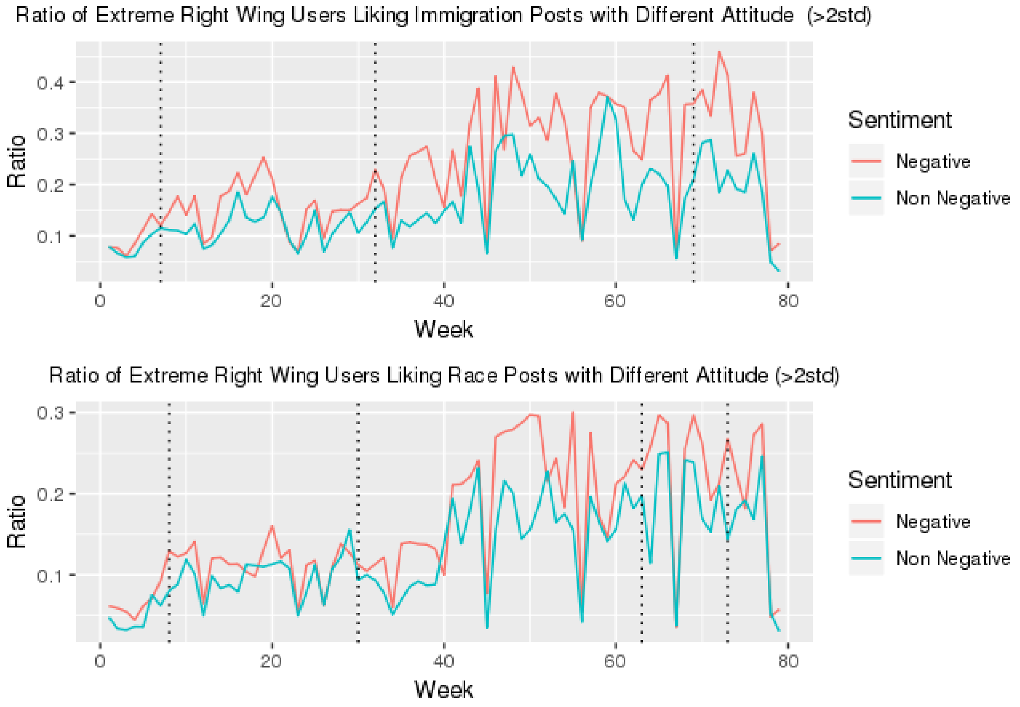

Figure 40: Ratio of Far-Right Politics Liking Related Posts

Notes: The time series here is basically same as the absolute value measure.

B.3 Extreme Users Commenting Immigration/Race Related Posts

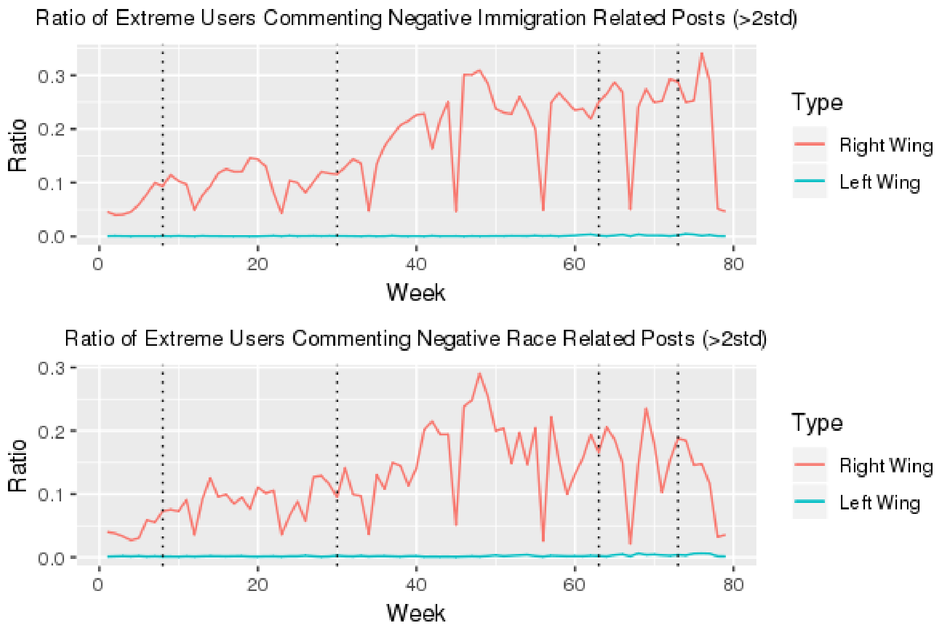

Figure 41: Ratio of Extreme Users Commenting Related Posts

Notes: The time series here is basically same as the absolute value measure.

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Figure 42: Ratio of Far-Right Politics Commenting Related Posts

Notes: The time series here is basically same as the absolute value measure.

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