The Role of Online Social Networks in Political Polarization

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Abstract

The body of knowledge suggests that online social networking has caused numerous societal, economic, and cultural changes. However, the impact of online social networking activities on politics and policy making has not been rigorously tapped. We intend to study the potential impact of online social networking activities of Members of the 113th House of Representatives on their voting behavior. To proceed with this goal, we have collected historical data from Twitter.com, Klout.com, U.S. Census Bureau, The Library of The Congress, and a number of political websites that provide archive of politicians' voting records. Although, further analysis is required for making any suggestions, our preliminary analysis signals the presence of homophily in the Congressmen’s social network. This study would inform the theory by shedding light on the dynamics of political polarization. This study may also inform the practice by revealing the potential impact of online social networks on politicians' voting behavior.

Keywords

Online social networking, political polarization, homophily, U.S. Congress

Introduction

Online social networking platforms provide informal conduits for individuals to express their interests, opinions, and ideas. The vast number of subscribers, the pushing force of friends, and the allure of standing out motivate the crowd to shine in the social networking platforms. Politicians however, employ social networking platforms as less formal channels through which they can express their ideas and beliefs with more limited concerns about the consequences. They also could use these channels to hear the voice of their constituents in a more convenient way. There are numerous Washington Post, Time Magazine, NY Times, and Economist articles about the extensive use of online social networks, especially Twitter, by politicians. A study by Greenberg (2012) revealed that nearly 98% percent of the congressmen are active users of online social networking platforms. Moreover, the analysis of the content of the posts by Members revealed that the majority of them are position taking posts. The question is though does the online social networking of the Members impact their voting behavior. More specifically, do these activities result in a more democratic policy making process or would cause more partisanship behaviors by the congressmen?

Communication cost perspective suggests that the cost of communication has been broken due to the emergence and proliferation of online communities. Hence, people are prone to be exposed to a variety of opinions, attitudes, or even cultures. This in turn may create a shared understanding among different-minded people and cause global homophily. On the other hand, researchers who focused on information processing capacity argue that due to the bounded processing capacity people behave selective in their collaborations. That is, individuals tend to interact with similar-minded people (Gu et al. forthcoming; McPherson et al. 2001). Since the technological innovations and emergence of online communities and social networking platforms made it easier and almost gratis for individuals to find and interact with like-minded people outside the geographical boundaries, Flache & Macy (2006) argue that the emergence of homophily in online communities is inevitable. Interaction with similar-minded people may in turn reinforce polarization and partisanship behaviors (Axelrod 1997; Sunstein 2007a). As Van Alstyne &
Brynjolfsson (2005) noted "[i]nternet users can seek out interactions with like-minded individuals who have similar values and, thus, become less likely to trust important decisions to people whose values differ from their own. This voluntary balkanization and the loss of shared experiences and values may be harmful to the structure of democratic societies as well as decentralized organizations." (Van Alstyne and Brynjolfsson 2005)

Ever increasing political polarization measured by McCarty et al. (2008) coupled with the warnings of thought leaders regarding the consequences of irresistible political polarization fueled this stream of research. One of the most interesting topics in this stream of research is the theoretical mechanisms of political polarization. Specifically, the role of social networking activities on the political polarization has allured a handful of researchers to tap this area. However, the results of these studies yield quite controversial findings. Therefore, the authors intend to study the impact of online social media activities of political elites on their voting behavior and the underlying theories behind this relationship. More specifically, we try to answer these questions:

1- How do Members’ online social networking activities influence their polarization in voting behavior?
2- How social media activities of Members’ friends influence congressmen's polarization in social media behavior?
3- How peers/competitors’ social media activities influence congressmen's polarization in social media behavior?
4- What moderates the relationships identified in 1, 2 and 3?
   a. Does constituents’ political polarization moderate the relationships identified in 1, 2, and 3?
   b. Dos party affiliation moderate the relationships identified in 1, 2, and 3?

Literature Review

The evolution of American party polarization over time has been studied thoroughly in the literature. Polarization in this area is interpreted as the ideological difference between Democrats and Republicans. The research in this area reveals that the two major parties were being converged until mid-70s. After that, an ever-increasing gap between two parties (Figure 1) has been emerging. That is, Republicans have been moving further toward the conservative perspective while Democrats have become further liberal (McCarty et al. 2008).

The Causes of Political Polarization

This stream of political science research addresses the major causes of political polarization in American policy making. Layman et al. (2006) studied the causes of party polarization in the U.S. Congress. Disagreements on critical issues and cultural and moral concerns, as Layman et al. (2006) maintained, are the major causes of party polarization in US politics. Carmines & Stimson (1989) argued that during 60s and 70s civil right movements and the dramatic differences between Democrats and Republicans initiated the ever increasing American political polarization. The term “issue evolution” coined by Carmines & Stimson (1989) refers to the polarization as a result of differences between Democrats and Republicans with regard to a set of important issues. Other issues that triggered party polarization were related to cultural and moral concerns. Among them, one may include abortion, homosexual rights and school payers (Abramowitz and Saunders 2008). In a sense, some of the researchers in this area believe that critical issues, cultural, and moral concerns trigger polarization in US politics. However, other researchers such as Cass R. Sunstein (Sunstein 2007a), Giovanni Sartori (Sartori 2005), and Robert Axelrod (Axelrod 1997) argue that polarization is an inevitable phenomenon. This perspective believes that the structure of the society and the principle of homophily majorly cause polarization (Axelrod 1997).
One of the most influential studies in this stream was performed by Axelrod (1997). He employed adaptive agent-based modeling to study dissemination of culture and polarization in societies over time. Axelrod’s model reveals that how interactions of agents (individuals) could result in polarization in the society. He suggests that agents’ interactions tend to be more frequent and influential when they are similar to each other. As Rogers (1983) stated based on Homans’ *The Human Group* seminal work, “The transfer of ideas occurs most frequently between individuals ... who are similar in certain attributes such as beliefs, education, social status, and the like.” (Rogers 1983: p278) In this perspective, the principle of homophily is responsible for polarization. That is, like-minded individuals tend to interact with each other more frequently and more influentially. Therefore, they become even more similar over time and form groups. The similarity between the individuals within a group separates them from other groups. As Sunstein (2007a) suggested, group polarization increases when people have a shared sense of identity. Especially in cases that group members argue against another group, they tend to reveal more extreme opinions. In this sense, homophily contributes to polarization.

Sunstein (2007a) categorizes the causes of polarization in three cohorts: the first and foremost cause is related to informational influences. Sunstein argues that initial seeds of all groups are initially biased. This inclination attracts like-minded people to the group. As members listen to the discussions, they tend to lean more toward the initial inclination of the seed. Hence, extreme point of view is the result of the discussions of similar-minded group members over time. The second cohort is related to social comparison. We like to be liked. What we say is sometimes a function of what we want to be perceived from us by other people (mostly people who are important to us). If leaning toward an extreme opinion is valued by others, group members may become more leaned toward that extreme to get more credit from others. The third cohort is related to confidence. “Agreement from others tends to increase confidence.” (Sunstein 2007a) More confidence in turn may make people more extreme.

Sartori’s perspective on polarization is quite simple. He argues that depending on the size of a group and the context the group members’ point of view is not a unique point. Instead, it is a spectrum with a mean in the center. He maintains since the center opinion in the group is already occupied, a new group member or a group member who seeks a better status in the group tends to take extreme positions within the spectrum to attract others. Repetition of this mechanism by new members joining the group over time gradually changes the average of the group toward an extreme point of view (Sartori 2005).
Online Social Media and Political Polarization

Sunstein (2001) argues that internet technology enabled people to easily filter what they want to see, hear, or read. Nowadays, everyone is able to design her own newspaper, magazine, and TV channels. For instance, if someone is interested in a certain point of view in politics, she may restrict herself to hear only from people with the same perspective. “With the reduced importance of general interest in magazine and newspaper, and the flowering of individual programming design, different groups make fundamentally different choices.” (Sunstein, 2001: p5) As Sunstein maintains, with the unlimited power of FILTERING, individuals can create their own COMMUNICATION UNIVERSE. Customization features available in many online media further strengthens self-filtering phenomenon. Many websites can choose what we are interested in just by knowing a little about us and our taste (Sunstein 2007b). These websites then can suggest recommendations based on the tastes of like-minded people. Therefore, polarization increases due to the current recommendation systems which are salient in online social networks.

Research hypotheses

According to Powell & Fazio (1984), repeated attitude expressions increase the accessibility of the attitude. Increases in accessibility in turn lead to greater attitude–behavior consistency (Fazio and Williams 1986). Drawing from Fazio’s studies, Downing et al. (1992) proposed that repeated expressions are at least partly responsible for attitude extremity. This proposition was further studied and supported by Brauer et al. (1995). More specifically, another study by Binder et al. (2009) based on the data from a nationwide mail panel survey carried out between 2002 and 2005 revealed that political talk plays a substantial role in shaping and polarizing attitudes on a given issue, with discussion in networks composed of like-minded others leading directly to the development of extreme attitudes. As Brauer & Judd (1996) concluded, the social psychology literature suggests that “individuals polarize in group discussions in part because they frequently express their own opinions and arguments as well as listen to the arguments and opinions of other group members.”

If we suppose that the Democrats shape one group and the Republicans shape another group, within-group political discussions would cause political polarization. Based on the social psychology literature and assuming the presence of homophily in online social network of congressmen we can propose that:

H1: Posting party-preferred political tweets by congressmen is associated with higher levels of partisanship behavior thus higher polarization of the congressmen.

H2: Being exposed to party-preferred political tweets posted by the affiliated group members increases political polarization of the congressmen.

Based on Sartori’s perspective on polarization and Sunstein’s social comparison cohort, a new group member or a group member who seeks a better status in the group tends to take extreme positions within the spectrum to attract others (Sartori 2005). Therefore it is hypothesized that:

H3: Congressmen from states with more polarized House Members post more extreme tweets in favor of their affiliated party.

Data and Variables

Twitter.com

Using a script in Python programming language, we have been collecting data from Twitter API since September 21, 2013. The current data set contains more than 106,000 tweets posted by Members of the 113th House of Representatives. Moreover, the counts of followers, tweets, and followings (friends) have been captured weekly. The dataset also includes the date, time, count of retweets and favorites, and the platform (web, mobile, etc.) for each tweet posted by Member and the lists of all of the Members’ friends on Twitter (lists of users being followed by the congressmen). Furthermore, we intend to collect all of the tweets posted by congressmen’s friends.

Such network is illustrated in Figure 2.
Klout.com

Klout.com provides a free service that measures the online social networking engagement of any given user. The exact algorithm of this measure is considered to be trade secret and not available to the researchers. However, Klout.com is the industry leader in rating online social networking engagement and offers the most widely used measure. The key feature of the Klout score is that this score is developed based on user’s activities on a variety of social networking platforms such as Facebook, Twitter, Google+, Youtube, LinkedIn, and Flicker. Another important feature of Klout score is that it is developed not only based on user’s own activities, but also other users’ reactions to her activities. For instance, a user whose tweet is retweeted for many times gets a better Klout score compared to someone whose tweets do not get retweeted. Because of these features of the Klout scores, we have collected Klout scores of Members every week since September 21st, 2013 by developing a script in Python programming language. The Klout scores may be employed in future analysis for generalization purposes or robustness checks.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Source of DATA</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>1- Congressmen’s tweets, 2- list of Congressmen’s friends, 3- Tweets by Congressmen’s friends 4- number of tweets posted by the Member per week, 5- number of followers per week, 6- number of followings (friends) per week</td>
<td>Twitter.com (API)</td>
<td>Weekly</td>
</tr>
<tr>
<td>7- Klout scores: A measure for online social networking engagement</td>
<td>Klout.com (API)</td>
<td>Weekly</td>
</tr>
<tr>
<td>8- W-NOMINATE score: A measure for Members’ ideological polarization based on their roll call votes</td>
<td>The Library of Congress (THOMAS), Voteview.com</td>
<td>Weekly</td>
</tr>
<tr>
<td>9- Ideology score: A measure for Members’ ideological polarization based bill co-sponsorships, 10- party memberships</td>
<td>Govtrack.us</td>
<td>Weekly</td>
</tr>
<tr>
<td>11- Human Development Index per state (HDI), 12- State population, 13- No. and % households have internet access, 14- No. and % individuals have internet access.</td>
<td>U.S. Census Bureau</td>
<td>Once</td>
</tr>
<tr>
<td>15- Partisan Voter Index (PVI): a measure for the constituents’ political polarization</td>
<td>Cookpolitical.com</td>
<td>Once</td>
</tr>
<tr>
<td>16- Member’s Districts, 17- Member’s age, 18- Member’s life expectancy, 19- Member’s race or ethnicity, 20- Member’s gender, 21- Member’s highest degree level, 22- Member’s type of degree, 23- Member’s a licensed lawyer</td>
<td>The Social Science Research Council</td>
<td>Once</td>
</tr>
</tbody>
</table>

Table 1. The variables and the sources of data
Ideological Polarization

One of the most dominant approaches for measuring ideological polarization in political science is the approach adopted in (McCarty et al. 2008, 2009). In this approach, DW-NOMINATE (dynamic, weighted, nominal three-step estimation), W-NOMINATE, and NOMINATE can be employed to measure ideological polarization. As Poole & Rosenthal (2000) stated, NOMINATE scores represent legislators’ overall voting tendencies on the traditional liberal-conservative dimension. Members who vote similarly on the same set of bills tend to get similar NOMINATE scores, while Members with different voting behavior get scores further away from each other.

Based on the weekly roll call votes retrieved from The Library of Congress (THOMAS), W-NOMINATE score of each Member for each week has been estimated and included in the data set.

We also collected data from other sources such as United States Census Bureau and The Social Science Research Council. Table 1 summarizes the variables and the sources of data.

Next Steps

Testing H1

So far, we have collected more than 106,000 tweets posted by the Members of The 113th House of Representatives. Since the content of the tweets vary, they may not have the same impact on political orientation of the Member. For instance, some of the tweets may be quite personal while some other reveal a very important opinion of the Member. Moreover, some of the tweets are in line with the political orientation of Member’s party while some other might be against the proposed position of Member’s party. To rigorously extract the politically relevant tweets by the Members, the literature suggests a coding procedure (Greenberg 2012). In this procedure, each tweet will be coded based on purpose, sentiment, and reference to the party. Based on purpose, each tweet can be classified into one of the following categories: 1- campaign-related tweets, 2- tweets about official congressional actions, 3- position taking tweets, 4- policy statement tweets 5- district or state related tweets 6- media or public relations tweets, 7- personal tweets, and 8- others. A tweet can also have a positive (+1), negative (-1), or neutral sentiment (0). A tweet may refer to congressman’s own party (+1), the opposing party (-1), or none of them (0). Table 2 represents a snapshot of the output of the coding procedure.

Testing H2

To be able to test the second hypothesis, we need to collect all of the tweets being exposed to the congressmen. It is worth mentioning that each Twitter user is fed only by the tweets posted by users she follows on Twitter. Therefore, it is a fair assumption to say that congressmen are only exposed to the tweets by users they follow. Based on our data, Members follow an average of 4,123 users on Twitter. Since there are 414 congressmen in the current dataset, a maximum of 1,706,922 twitter users need to be included in our data. Due to Twitter API rate limits, collecting the tweets posted by all of these users seem to be challenging. Moreover, following a user on Twitter is not necessarily equivalent to reading her tweets. Therefore we decided to collect all of the tweets from users whom have been mentioned or retweeted by the congressman in her latest 200 tweets. This condition will ensure that the dataset only includes the tweets from users who received some attention from the congressmen and helps us to overcome Twitter rate limit issue. Based on this criterion, we have identified 18,081 unique Twitter users who have been mentioned in Congressmen’s tweets. Current Twitter API policy would allow us to collect the last 200 tweets posted by each user, which results in 3,616,200 tweets overall.

In reality this number would be smaller because Members’ following lists have some users in common.
Table 2. Snapshot of the output of the proposed coding procedure

<table>
<thead>
<tr>
<th>Congressman</th>
<th>Tweet</th>
<th>Sentiment</th>
<th>Reference</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kevin Brady (R-TX 8th District)</td>
<td>&quot;The cancellations lay bare 3 pillars of #Obamacare: (a) mendacity, (b) paternalism and (c) subterfuge.&quot; <a href="http://t.co/fHBut21LAE">http://t.co/fHBut21LAE</a> @krauthammer</td>
<td>Negative</td>
<td>Opposing party ³</td>
<td>-1</td>
</tr>
<tr>
<td>William Keating (D-MA 9th District)</td>
<td>&quot;Great to join @mayorflanagan @senwarren @repjoekennedy for the announcement of #COPS grant- that will put officers on the job in #FallRiver.&quot;</td>
<td>Positive</td>
<td>Same party</td>
<td>+1</td>
</tr>
</tbody>
</table>

Since not all of the tweets by these users have a political content, we need to extract politically relevant tweets. Given the size of this dataset, manual coding of all of the tweets by congressmen’s friends seems to be quite challenging. Therefore, we intend to perform text mining and sentiment analysis to extract and code politically relevant tweets. A political tweet can be defined as a tweet that includes at least one political hashtag. To identify an appropriate set of political hashtags, we need to perform a tag co-occurrence discovery procedure as instructed by Conover et al. (2011). By employing this procedure as well as text mining, we could extract the relevant tweets posted by Twitter users who are followed by the Members. The next step would be performing sentiment analysis. It is worth mentioning that the manually coded tweets in the previous procedure may be employed to train the classifier for this procedure. To identify the reference of the tweets, we could employ hashtags again. According to Conover et al. (2011), it is possible to identify the reference of the tweets by defining two different sets of hashtags: 1- hashtags that commonly refer to conservatives and 2- hashtags that commonly refer to liberals.

**The Econometric Model for Testing H1 & H2**

One of the best methods for analyzing panel data in the Econometric literature is the fixed effect model. Since fixed effect models’ estimates are based on the differences between observed values and the temporal means, they require time-variant variables. In our model though, some of the variables are time-invariant (Age, Party, and PVI). There are different approaches to deal with this situation. One of the rigorous econometric models that allows both time-variant and time-invariant variables in the model was proposed by Hausman & Taylor (1981). Hausman and Taylor proposed the following econometric model to allow both time-variant and time-invariant variables in the model:

³ Since Rep Kevin Brady (R-TX 8th District) who posted this tweet is a Republican, this tweet refers to the “opposing party”.
It is worth mentioning that the Hausman-Taylor estimator assumes that some individual-specific unobservable effects are correlated with some other explanatory variables. Based on the Hausman-Taylor econometric model we developed the following econometric model:

\[ y_{it} = x_{1it}^T \beta_1 + x_{2it}^T \beta_2 + z_{1i}^T \alpha_1 + z_{2i}^T \alpha_2 + \epsilon_{it} + u_{it}, \]

where

- \( x_{1it} \) is \( K_1 \) variables that are time varying and uncorrelated with \( u_i \),
- \( z_{1i} \) is \( L_1 \) variables that are time-invariant and uncorrelated with \( u_i \),
- \( x_{2it} \) is \( K_2 \) variables that are time varying and correlated with \( u_i \),
- \( z_{2i} \) is \( L_2 \) variables that are time-invariant and correlated with \( u_i \).

The assumptions are

\[ E[u_i | x_{1it}, z_{it}] = 0 \text{ though } E[u_i | x_{2it}, z_{2i}] \neq 0, \]
\[ \text{Var}[u_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \sigma_u^2, \]
\[ \text{Cov}[\epsilon_{it}, u_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = 0, \]
\[ \text{Var}[\epsilon_{it} + u_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \sigma^2 = \sigma^2_e + \sigma_u^2, \]
\[ \text{Corr}[\epsilon_{it} + u_i, \epsilon_{it} + u_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \rho = \sigma^2_e/\sigma^2. \]

Testing \( H_3 \)

For testing \( H_3 \), a measure of the extremity of the tweets posted by the congressmen should be developed. It can be done by multiplying the sentiment of the tweet by the reference of the tweet according to table 2. For instance, for the first tweet in table 2 the result will be \((-1) \times (-1) = 1\). We call this measure Valence of tweet. For each congressman, we will calculate the average of the Valences of the tweets posted by her during the given time period and call it the Valence of congressman. With this procedure, a valence score for each congressman can be developed. The next step is to employ a hierarchical model to test the third hypothesis. In this model, Valence of congressman would serve as the response variable.

Further Analysis

We believe that there a number of questions worth asking from the practitioners’ perspective that can be addressed by further analysis of data. For instance, does constituents’ political polarization moderate the relationships identifies in \( H_1, H_2, \) and \( H_3 \)? Or, does party affiliation moderate the relationships identifies in \( H_1, H_2, \) and \( H_3 \)? Since we could not yet locate a solid theoretical suggestion for the potential impact of party or constituents’ political polarization on the relationships described in \( H_1, H_2, \) and \( H_3 \), they did not propose a particular hypotheses. However given the interest of practitioners in these questions, we could easily reveal the moderating impact of party affiliation or constituents’ political polarization (as measured by PVI) in \( H_1, H_2, \) and \( H_3 \). This can be done simply by adding the interaction terms in the Hausman-
Taylor model in H1 and H2 or the multilevel model in H3. Another interesting exercise would be to divide Members’ friends into three groups: 1- Friends who are official politicians (e.g. Senators or Governors), 2- Friends from the media (e.g. Reporters), 3- non-affiliated friends (e.g. constituents). It would be interesting to find tweets by which of these groups have the highest impact on Members’ polarization if any.

**Congressmen Twitter Network**

One of the most interesting parts of this research is to study the presence of homophily in the congressmen online social network. To build a network of congressmen connections based on Twitter following/follower relationships, we extracted the lists of all Twitter users followed by each congressman (as described in section 2.3.1). Then, all of the Members’ Twitter screen names were checked against all of those lists. The result of this procedure is a directed network of the congressmen following/follower relationships on Twitter. Figure 2 represents such network developed in NodeXL. It is worth mentioning that the blue nodes are Democrat congressmen and the Red nodes are congressmen from the conservative party. The arrows are pointed at nodes being followed. Except for few exceptions such as Denny Heck [Dennis Heck (D-WA 10th District)], the majority of the Members are following/being followed by Members from their affiliated party. This indeed signals the presence of homophily in online social network of the congressmen.4

**Discussion & Conclusion**

This manuscript is a report of an ongoing research that attempts to tap the relationship between social networking activities and the political polarization. The scope of this research however, is limited to the political elites in the United State of America (Members of the 113th House of Representatives). By collecting Members’ data through crawling their Twitter pages, GovTrack.us, Voteview.com, US Census, Library of the Congress (THOMAS), klout.com, and other sources of data the authors have created a panel dataset to study the relationship between their polarization and twitter activity. The theoretical background for this relationship is twofold: 1- Communication Cost perspective suggests more cross party relationships and therefore a less polarized community. 2- On the other hand the presence of homophily in the online social network of Congressmen suggests higher levels of within party interactions which would result in higher levels of partisanship and polarization. The first camp basically does not demand any changes in the online social networking behavior of the politicians since this perspective suggests that politicians are already exposed to a variety of ideas (same party and opposing party) therefore they make informed decisions. On the other hand, the information processing capacity and homophily perspectives suggest that politicians’ online social media interactions are bounded to communications with homophilous groups (same party). Therefore, politicians need to be exposed to a variety of ideas to be able to make more informed decisions that reflect the interest of the society.

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4 It is worth noting that NodeXL graphed the network solely based on the edges. No information about party affiliation was provided.
We do believe that the findings of this study could be quite informative for both the scientists and the practitioners. Hypotheses 1 and 2 would shed light on the theoretical dynamics of polarization by tapping the impact of self-activities (H1) and the impact of friends’ activities (H2). For practitioners and politicians, it is important to understand the potential impact of online social activities on political partisanship. If indeed politicians’ online social media engagement is associated with their voting behavior and political polarization, a mechanism for being exposed to a variety of ideas that reflects the whole society not only one political party would be in place. There is no doubt that Members of the U.S. Congress are among the most influential figures not only in the U.S. but also in the world. Moreover, their voting behaviors could impact the daily lives of millions of people. Therefore, studying the causes of their voting behavior may have an immense impact on the society. Given the fact that nearly 98% of Members are active users of online social networks, the impact of online social networking on voting behavior could be salient.
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