The Impact of Twitter Adoption on Decision Making in Politics

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Abstract

Organizations have used social media extensively to engage customers, but little is known whether such engagement truly influences organizations’ decisions to make them closer to their customers. This paper studies this question in a unique context – the impact of adoption of Twitter on U.S. Congressmen’s voting behavior. In particular, we consider whether the adoption makes Congressmen to vote more in line with the political orientation of their constituents. We constructed a panel data for 442 Members of the 111th U.S. House of Representatives across a period of 24 months. We exploit the variation in joining Twitter across Congressmen to identify the impact of joining Twitter on voting behavior. Using a fixed effect model, we found that the adoption of Twitter makes Congressmen to vote more in line with their constituents. That is, in districts where Congressmen are more conservative than the constituent Twitter adoption results in less conservative votes by Congressmen. Similarly, in districts where Congressmen are more liberal than the constituent, Twitter adoption results in less liberal votes by the Congressmen.

1. Introduction

Online social networking platforms are profoundly changing the way we communicate, collaborate, and make decisions. The enormous impacts of these platforms on the societies can be observed in numerous examples: microblogging platforms such as Twitter which have been widely credited as a key enabler of Arab Spring, Spain and Portugal movements in 2011, and more recently Turkey and Brazil movements in 2013.

Moreover, online social media and social networks facilitate the participations of consumers and the public in business [1], [2] and government decision making processes [3], [4]. However, little is known about the degree to which such participations truly affect decision outcomes. While organizational decisions are often not observable to the public and difficult to quantify, the U.S. political system provides a rare exception where the most important decisions taken by U.S. politicians – voting decisions – are observable to the public and have been carefully analyzed and quantified by political science experts. Furthermore, because of their influence, online social networking platforms have been extensively adopted by political figures. The low cost of adoption and the expansive reach have convinced almost every American politician to be active in these platforms. A 2012 study by Greenberg revealed that nearly 98% percent of the U.S. Congressmen are active users of online social networks [5]. Moreover, the analysis of the content of the posts by Congressmen revealed that the majority of them are position taking posts. It is almost unimaginable, nowadays, to find a candidate running for a political office without creating a social networking campaign. Online social networking by politicians not only communicate their messages to the constituents, but also provides the constituents a channel to interact with their representatives in a convenient and casual way. Furthermore, the fact that these conversations are publicly available to other constituents creates a dynamic system that facilitates transparency and accountability. Hence, the adoption of online social networks by politicians could facilitate the influence of constituents on the political process. Therefore, in this research, we use the U.S. Congressmen’s voting decisions to assess to what degree the public influences organizational decisions through online social media. Specifically, we examine how the adoption of online social networking influences politicians’ voting orientations. Further, we examine whether the adoption of online social networking moves politicians’ voting orientations closer to the views of their constituents.

The organization of this paper is as follows. Section 2 reviews the literature of online social networking and its impact on decision making. We present our data and variables in Section 3. The focus is on our empirical model in section 4. In Section 5, we present descriptive statistics along with the results of our analyses. We discuss our findings and conclude with limitations and potential extension of this study in the next sections.

2. Literature Review

The towering interest of IS researchers in the realm of online social networking during last few years provided the IS literature with genuine, rigorous examples of research studies in social media domain.
The objective of these studies, in a broad sense, can be divided to two categories: studies that focus on consumer activities in social media, and studies that focus on how social media influences firm and organization decisions.

Yan and Tan [6] studied the impact of involvement in an online healthcare social community on patients’ mental health. Their results suggested that patients who are active on the social networking platform gain benefits from learning from other users. Learning from other patients helps the users in the self-management processes and therefore is associated with better health outcomes. According to Wu [7], information-rich networks can influence the decisions made by users. Burt [8] theorized that three distinct information benefits drive this effect: access, timing, and referrals. An information-rich network would allow the users to access more information in a timely manner. Furthermore, the users can obtain recommendations from trusted acquaintances. These mechanisms may change the users’ decisions and, therefore, their performance [7]. These findings are in line with similar studies in other disciplines. Marketing literature for instance hosts extensive research studies about the influence of word-of-mouth in online social networking platforms on the purchasing decisions. Through a unique natural experimental setting resulting from information policy shifts at Amazon.com, Chen et al. [9] studied the impacts of online reviews on consumer choices and revealed that word of mouth and observational learning may influence consumer behavior. In another study, Goh et al. [10] found that engagement in social media brand communities leads to a positive increase in purchase expenditures. By analyzing the communications among the users, Goh and colleagues concluded that social media contents could impact consumer purchase behavior through embedded information and persuasion. The influence of social media activities on consumer behavior has also been studied by Rishika et al. [11]. The results of this study further supported the positive influence of customer participation in a firm’s social media efforts on the frequency of customer visits and, therefore, firm’s profitability.

The second stream of studies emphasizes on the influence of social media on firm and organization decisions. Wu [7] revealed that the adoption of a work-related social networking tool may impact employees’ decisions and performance. By studying the changes in employees’ networks and performance before and after the introduction of a social networking tool, she revealed that the adoption influenced the quality of the decisions and, therefore, employees’ performance. Luo et al. [12] studied the relationship between social media and firm equity value using vector autoregressive models. Their results suggested that social media-based metrics (web blogs and consumer ratings) are significant leading indicators of firm equity value and have a faster predictive value than conventional online media. These findings support the transformative power of social media as noted in [13].

Overall, the majority of studies in this area have focused on the network attributes of social media or the flow of information within the networks. A new user who joins a network has the opportunity to seek new information within the network. Whether the user is a patient who seeks relevant information to deal with the illness, or a buyer who seeks information about a certain type of product, information-rich networks could help them in achieving their goals. For politicians, an information-rich network is a network that allows them to seek information about the citizens. After all, politicians are representing the citizens and need their votes to sustain. We believe that online social networks can be regarded as information-rich networks for politicians since these networks contain overwhelming information about the citizens, their behaviors, and their preferences.

3. Data

To study the impact of the adoption of online social networking on the voting behavior of politicians, we constructed a panel data for 442 Members of the 111th U.S. House of Representatives across a period of 24 months using 3 disparate datasets. Summary statistics of the dataset are represented in Table 1.

Spanning the 111th Congress, we estimate the monthly measure of Congressmen’s political orientation based on votes cast by each Congressman in a given month. We use Weighted Nominal Three-Step Estimation (WNOMINATE), a widely used estimation model in political science, for our estimation [14]. WNOMINATE is “a scaling procedure that performs parametric unfolding of binary choice data.” [15] Given a matrix of binary choices by individuals (for example, Yea or Nay) over a series of Parliamentary votes, WNOMINATE produces a configuration of legislators and outcome points for the Yea and Nay alternatives for each roll call using a probabilistic model of choice. WNOMINATE creates a spectrum of scores ranging from -1 to +1, with -1 representing the most Liberal Congressman and +1 representing the most Conservative Congressman (Figure 1). It is worth mentioning that the WNOMINATE scores have been employed by numerous social scientists to study the behaviors of the politicians based on their voting records [16]–[18].

111 Congress
To capture the dates Congressmen adopted Twitter, we made API calls to Twitter API and Sunlight Foundation’s Congress API, which helped us to link Congressmen’s Twitter accounts to their legislative data. Out of 442 Congressmen, 246 had Twitter accounts by the time we made the calls. Among the 246 Congressmen, 189 joined Twitter during the 111th Congress (January 2009 – December 2010). With this data, we constructed a binary twitter adoption indicator for a Congressman for a given month. For every month, the value of this binary variable is 1 if the Congressman joined Twitter before or during that month and zero otherwise.

We adopted Cook’s partisan voting index developed and introduced by Charlie Cook in 1997 as a measure of constituents’ political orientation. Cook’s PVI is a measurement of how strongly a United States congressional district leans toward the Democratic or Republican Party, compared to the nation as a whole. Cook employs the last two presidential election results as a baseline for gauging the political orientation of each congressional district [19], [20]. We obtained Cook’s PVI for each congressional district during 111th Congress. Cook’s PVI for the 111th Congress ranges from 0 to 29 for Republican states and from 0 to 41 for Democrat states. During the 111th Congress, New York’s 15th and 16th districts with a PVI score of D+41 were the most liberal districts while Alabama’s 6th and Texas’s 13th districts with a PVI of R+29 were the most conservative districts. We rescaled Cook’s PVI to match our WNO M INATE measures. In our dataset Cook’s PVI ranges from -1 to +1 with -1 being the score for the most liberal congressional district and +1 being the score for the most conservative district.

4. Empirical Methodology

The adoption of Twitter by Congressmen over time creates a natural experiment setting that allows the comparison of difference in voting behavior before and after joining Twitter. We exploit the variation in joining Twitter across Congressmen as the basis for identifying the impact of adopting Twitter on voting behavior. This strategy has been implemented in numerous research studies including [21]–[23]. To assess the effect of Twitter adoption on Congressmen’s voting behavior, we employ the following fixed effect model:

\[ y_{it} = \beta x_{it} + \alpha_i + T + u_{it} \]  

Specification (1)

where \( i \) is the index for Congressmen and \( t \) is the index for time, \( T = 01-2009, 02-2009, \ldots , 12-2010; y_{it} \) is Congressman \( i \)’s political orientation at time \( t \); \( x_{it} \) is the binary variable for adopting Twitter, meaning that \( x_{it} = 1 \) if Congressman \( i \) has a Twitter account at time \( t \) and zero otherwise; \( \alpha_i \) is the fixed effects for Congressman \( i \), \( T \) is a vector of time fixed effects. In this model, \( \beta \) is the difference-in-difference estimate of
the impact of adopting Twitter on voting behavior of Congressmen. If \( \beta > 0 \), then joining Twitter has caused the Congressmen to vote more conservatively. If \( \beta < 0 \), joining Twitter has caused the Congressmen to vote more liberally. The congressman fixed effects control for observed and unobserved variations across Congressmen such as age, gender, longevity of service, and constituents’ characteristics.

To assess whether the adoption of Twitter makes congressmen to vote more in line with the political orientation of their constituents, we add a moderating variable (Figure 2) to measure the political difference between each congressman and his constituents to Specification (1):

\[
y_{it} = \beta_1 x_{it} + \beta_2 x_{it} \times P_i + \alpha_t + T_{it} + u_{it}
\]

where \( P_i \) is the political difference between Congressman i and his constituent. We obtained \( P_i \) by calculating the difference between the mean of W NOMI NATE scores of Congressman i over time periods \( t = 0, 1, \ldots, t^* - 1 \) and his district’s PVI. Here, \( t^* \) is the time period during which Congressman i joined Twitter. In other words, \( P_i \) is the difference between political orientation of Congressman i and that of his constituent prior to joining Twitter. A positive \( P_i \) value denotes that Congressman i is more conservative than his constituent, and a negative \( P_i \) denotes that Congressman i is more liberal than his constituent.

Table 1. Summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Congressman’s political orientation (W NOMI NATE)</td>
<td>9724*</td>
<td>0.011</td>
<td>0.547</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Twitter adoption</td>
<td>10680</td>
<td>0.404</td>
<td>0.491</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Constituent’s political orientation (Cook’s PVI)</td>
<td>10680</td>
<td>0.039</td>
<td>0.414</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>Political difference</td>
<td>9724</td>
<td>-0.045</td>
<td>0.266</td>
<td>-0.658</td>
<td>0.507</td>
</tr>
</tbody>
</table>

*We did not include W NOMI NATE estimates for August 2009 and August 2010 due to Congress Recess.

5. Results

Table 1 presents the summary statistics for the dataset. The mean and standard deviation for Congressman’s political orientation is consistent with prior studies [14]. The positive mean of Congressman’s political orientation denotes that the 111th Congress was slightly leaned toward conservative edge of the political spectrum. Twitter adoption is a binary variable and equals to zero if the Congressman does not have a Twitter account and 1 otherwise.

As explained earlier, we employed Cook’s PVI as a measure of Constituent’s political orientation. Cook’s PVI has been rescaled to match W NOMI NATE scores. Similar to W NOMI NATE, Cook’s PVI ranges from -1 to +1 with -1 being the most liberal district and +1 being the most conservative district. The positive mean of constituent’s political orientation denotes that the constituents were slightly leaned toward the conservative edge of the political spectrum during the 111th Congress.

Political difference is obtained by subtracting constituent’s political orientation from the temporal mean of Congressman’s political orientation before the Twitter adoption. The negative mean of this variable denotes that the Congressmen were slightly more liberal than the constituents. Political difference ranges from -0.658 to +0.507. As noted earlier, the larger the political difference value, the more conservative the Congressman as compared to the constituent. The smaller the political difference value, the more liberal the Congressman as compared to the constituent.

According to table 2, the constituents of Congressmen who adopted Twitter during the 111th Congress had a mean political orientation of 0.028. The constituents of Congressmen who did not adopt Twitter at all during the 111th Congress had a slightly higher mean political orientation (0.053) meaning that the adoption of Twitter by Congressmen from less conservative districts was slightly higher than that of Congressmen from more conservative districts.
Table 2 also reveals interesting information about the Congressmen’s political orientation. Compared to non-adopters, eventual adopters had much lower mean political orientation before they adopted Twitter. However after the adoption, they had a higher mean political orientation. That is, adopters became more conservative after joining Twitter. Comparison of the means between Congressmen and constituents in adopters’ districts reveal that the difference between Congressmen and their constituents diminished after the adoption. According to table 2 however, the absolute value of the difference is still smaller in the non-adopter districts.

Table 3 represents the main results of our empirical analysis. Model 1 and Model 2 are based on Specification (1). The difference between Model 1 and Model 2 is the inclusion of time-fixed effects in Model 2. Twitter adoption is positive and significant in both models. That is, joining Twitter is associated with the Congressmen becoming more conservative.

Model 3 and Model 4 are based on Specification (2) in which we included the interaction term between Twitter adoption and political difference. We included the time-fixed effects in Model 4 but not in Model 3. Although Twitter adoption is not significant in Model 4, the interaction between political difference and Twitter adoption is negative and significant. That is, political difference moderates the relationship between Twitter adoption and Congressmen’s political orientation. Model 4, which includes the interaction term and the time-fixed effects, is the research model of this study as represented in Figure 2. According to the results of Model 4, Twitter adoption is not significant anymore. Instead, the interaction between twitter adoption and political difference is significant and negative. This means, after Twitter adoption, the political difference between Congressmen and the constituent shrinks. Put it differently, Congressmen behave (make decisions) more in line with their constituents after adopting Twitter.

To test for heteroskedasticity we exploited modified Wald test for group-wise heteroskedasticity in fixed effects regression model. Since we identified the presence of heteroskedasticity, we employed Eicker-Huber-White robust standard errors in all models. To decide between random and fixed effect models, we employed Hausman test. The result was in favor of the fixed effect model (Prob>chi2 = 0.072). We also tested for the time fixed effects and identified the presence of time fixed effects. Therefore we generated time dummies to obtain the two level fixed effects estimators (Model 2 and Model 4).

We also tested for cross-sectional dependence using Breusch-Pagan LM test of independence and Pesaran cross-sectional dependence. Pesaran cross-sectional dependence test is used to test whether the residuals are correlated across subjects. Cross-sectional dependence can lead to bias in tests results (also called contemporaneous correlation). The results of our tests did not signal the presence of cross-sectional dependence. We further employed Wooldridge test for autocorrelation in panel data; which signaled the presence of serial correlation. Therefore we used clustered errors in all models.
Moreover, instead of the binary Twitter adoption variable, we employed a variable called Twitter experience. Twitter experience is simply equal to the common logarithm of the number of days Congressman has been active on Twitter plus 1 (ranges from 0 to 2.844 with a mean of 1.453 and 1.165 standard deviation).

We replicated our analysis by replacing Twitter adoption with Twitter experience in specifications 1 and 2. Table 4 represents the results of the analysis. According to Model 8 in Table 4, Twitter experience is not significant in our full model. The interaction between Twitter experience and political difference is significant and negative. This means that the difference between political orientation of the Congressman and that of his constituents shrinks as Congressman gradually gain experience using Twitter.

To further examine the impact of Twitter adoption on Congressmen’s political orientation and the political difference between Congressmen and their constituents, we performed another set of analyses based on Sun and Zhu [24]. We use the following specification to determine the impact of Congressmen’s Twitter adoption on political orientation:

\[ y_{it} = \beta_0 + \beta_1 Q_i + \beta_2 Q_i \times x_{it} + \sum_{j=1}^{24} \gamma_j MonthDummy_j + \epsilon_{it} \]

**Specification (3)**

where \( Q_i \) is a dummy that takes the value of 1 if Congressman i is an eventual adopter, and 0 otherwise. We call this variable “Adopter”. \( \beta_2 \) is our difference-in-differences estimator that captures the adoption’s effect on political orientation of the Congressmen. \( x_{it} \) is the binary variable for adopting Twitter, meaning that \( x_{it} = 1 \) if Congressman i has a Twitter account at time t and zero otherwise (This variable is the same as in Specifications 1 & 2, but this time instead of “Twitter adoption” we call it “Twitter status” to prevent confusion with variable “Adopter”). We run the model in Specification (3) with two different response variables. For the first response variable, we use Congressmen’s political orientation (the same as Specifications 1 & 2). For the second response variable, we use a variable called political misfit. To construct this variable, we calculate the Congressmen’s mean political orientation before the adoption and after the adoption. Then we subtract Cook’s PVI from each of these two values. Therefore, we will have one value for the political difference before the adoption and one value for the political difference after the adoption. Then, we calculate the absolute values of these values and call this variable political misfit. Political misfit, simply, measures the absolute difference between Congressmen’s political orientation and their constituents’ political orientation before and after the adoption. A decrease in political misfit means that Congressman is more aligned with his constituent in terms of political orientation.

We employed Eicker-Huber-White robust standard errors in all models. We also included dummies for each month from January 2009 to December 2010 to control for changes in all Congressmen’s propensity to shift in the Liberal-Conservative spectrum through changing their voting behavior. We further employed Wooldridge test for autocorrelation in panel data; which signaled the presence of serial correlation in models 9 and 10. Therefore we clustered the error terms at the Congressman level in models 9 and 10. We introduced Congressman-level fixed effects to control for time-invariant, unobserved Congressman characteristics. Fixed effects allow us to focus on changes in behavior over time for any given Congressman, rather than the absolute levels. Fixed effects, however, do not control for time-variant unobservables that may be correlated with the decision to adopt Twitter. These time-variant unobservables could lead, for example, to different trends over time for adopters and non-adopters. Therefore, we construct a time-variant instrumental variable to account for the effects of time-variant unobservables. Valid
For a Congressman who adopts Twitter during 111th Congress is around 2 percentage points less than that of a Congressman who does not. This percentage further decreases by an additional 3 percentage points after the Congressman adopts Twitter. Model 13 reports the results with fixed effects (FE), which are similar to those in Model 12. The variable Adopter drops from the regression, because its value does not vary over time. In both models 12 and 13, the coefficients of the interaction variable, Adopter × Twitter status, reflect the average effect of the adoption on the treated group. Model 14 reports the results with both fixed effects and instrumental variables using two-stage least-squares (2SLS). The results in Model 14 show that the adoption’s effect does not change much after we correct for endogeneity with the instrumental variable.

Table 6 provides first-stage estimation results for models 11 and 14 in Table 5 to illustrate the instrumental variable’s relevance. In models 15, we did not include the time-fixed effects. In Model 16, we added the time-fixed effects to the model. We find that the instrument is highly correlated with becoming a Twitter adopter, and these results are statistically significant at the 1% level in both models. The overall Wald chi-squared test or F-test for the instrument in each model is also highly significant.

6. Discussion

Social influence network theory suggests that a social network user’s initial opinion or behavioral assessment might change due to the information cascaded in the social network [27]. Furthermore, by communicating and interacting with one another, people create social influences that affect their opinions, attitudes, and behaviors [28], [29]. In this study we find that Congressmen’s presence in Twitter platform directs them toward the conservative side of the political orientation spectrum. According to figure 3, although
the politicians became more conservative due to their presence in Twitter sphere, their average political orientation has shifted toward the middle of the spectrum, which signals a higher political balance in the 111th House of Representatives. The comparison between the mean political orientation of the constituents with that of the adopters shows that Congressmen who adopted Twitter during the 111th Congress moved closer to their constituents in terms of political orientation.

The main finding of this study relates to the interaction between Twitter adoption and political difference (Model 4). This variable is significant and negative in our model. This means that in districts where the Congressman is more conservative than the constituent Twitter adoption results in less conservative voting behavior by Congressman. That is, the Congressmen adjusts their political orientation according to the constituents’ political orientation. Similarly, in districts where the Congressman is more liberal than the constituent, Twitter adoption results in less liberal behavior by the congressman. Again, the Congressmen are adjusting their political orientation according to the constituents. As nicely coined by Bartels [30], “the public tends to act as a thermostat”, as online social networking platforms enable the constituents to be heard by their representatives in the Congress.

Our findings in Model 4 and Model 8, have been supported by the results of models 9 through 14. According to the results of Model 11 in table 5, Congressmen who eventually adopted Twitter tended to shift toward the conservative spectrum even when we corrected for the endogeneity of adoption. Furthermore, the results of models 12 and 13 in table 5 reveals that the political misfit between Congressmen and their constituents shrinks as they adopt Twitter platform. The results of Model 14 in table 2, supports this finding even when we correct for the endogeneity of the adoption.

It is worth mentioning that although we do not have an estimate for political orientation of Twitter users, studies show that Americans deviated from liberalism and became more conservative during the 111th Congress [30], [31]. As figure 4 illustrates, American’s liberalism policy mood declined from 62.6% from 2008 to 58.2% in 2011. Meanwhile according to figure
5, the conservatism policy mood among Americans has been on the rise during the same period.

7. Conclusion

Previous studies suggest 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 adequately tapped. To pursue the goal of studying the impact of online social networking on the voting behavior of politicians, we constructed a panel data for 442 Members of the 111th U.S. House of Representatives across a period of 24 months using three disparate datasets. We collected the voting records of the Members, the date they created their Twitter accounts and their constituent’s political orientation. Using a fixed effect model, we revealed that adoption of Twitter by Congressmen directs them toward the conservative edge of political spectrum. Furthermore, we found that the relationship between adoption and orientation shift is moderated by the political difference between congressman and his constituent. That is, in case of a congressman whose political orientation is more conservative than that of his constituent, the adoption directs him toward the liberal spectrum to be more aligned with the constituent. In case of a congressman whose political orientation is more liberal than that of his constituent, adoption leads him to a more conservative point in the spectrum so that the congressman and the constituent are better politically aligned.

8. Limitations & Future Research

One of the limitations of this study is related to the sample. U.S. Congressmen are elite politicians whose decision making in politics would differ from regular citizens. Thus, generalizability of these findings shall be limited to the elite politician population.

To better extend the realm of this research, one may study the dynamic network of politicians in social media. Such network can be built based on friendships or conversations in online social networking platforms. A dynamic network analysis may shed more light on the underlying mechanism of influence on greater detail.

Another interesting extension of this study would be the study of the posts by Congressmen. A granular dataset that includes the actual social networking activities (e.g. tweets, number of friends, number of followers, ...) would allow the researchers to elaborate on the underlying mechanism of social media influence on political orientation and decision making.

Last but not least, a dynamic monthly measure for constituents’ political orientation could have helped us to construct a more accurate measure for political difference and political misfit. However, to our best knowledge, all of the measures developed for constituents’ political orientation are for four years or more time periods. It is worth mentioning that similar to Cook’s PVI the majority of these measures are developed, at least partly, based on the presidential elections data [34].

9. References


[30] L. Bartels, “Americans are more conservative than they have been in decades,” The Washington Post, 30-Sep-2013.


