Information Systems Research

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

The Impact of Twitter Adoption on Lawmakers' Voting Orientations

Reza Mousavi, Bin Gu

informs
http://pubsonline.informs.org/journal/isre/
INFORMATION SYSTEMS RESEARCH
Vol. 30, No. 1, March 2019, pp. 133–153
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

The Impact of Twitter Adoption on Lawmakers' Voting Orientations

Reza Mousavi,[a] Bin Gu[b]

[a] Belk College of Business, University of North Carolina–Charlotte, Charlotte, North Carolina 28223; [b] W. P. Carey School of Business, Arizona State University, Tempe, Arizona 85281

Contact: reza.mousavi@uncc.edu, http://orcid.org/0000-0002-1990-7767 (RM); bin.gu@asu.edu, http://orcid.org/0000-0002-0396-8899 (BG)

Received: November 11, 2015
Revised: November 24, 2016; October 4, 2017; February 26, 2018
Accepted: March 10, 2018
Published Online in Articles in Advance: January 28, 2019

https://doi.org/10.1287/isre.2018.0791

Abstract. Social media has been found to be influential in a variety of contexts. From mobilizing the crowd in social movements to helping refugees settle into a new country, social media has had a significant impact. This study examines the role of social media in Congressional representation in a democratic political system. We intend to assess the impact of U.S. Representatives' Twitter adoption on their *voting orientations* in the U.S. Congress. In particular, we consider whether the adoption of Twitter by representatives makes them vote more in line with the *political ideology* of their constituents. We constructed a panel data for 445 members of the 111th U.S. House of Representatives across a period of 24 months. We exploited the variation in joining Twitter across representatives to identify the impact of joining and using Twitter on *voting orientations*. Using fixed effects and difference-in-differences approaches, along with propensity score matching to address potential endogeneity in representatives' Twitter adoption decisions, we found that representatives' adoption of Twitter causes them to vote more in line with their constituents. Furthermore, the effect of Twitter adoption is more salient when a representative's party differs from the party affiliation of the constituent or when Twitter use per capita is higher in the representative's state. To identify the underlying mechanism of influence, we conducted further analysis on one of the important issues in the 111th Congress. Our results indicate that the volume of tweets directed at representatives signals the importance of certain bills to constituents. When representatives vote on bills that are the focus of a large volume of constituents' tweets, they vote in a manner more aligned with their constituents' opinions. Interestingly, the opinions the tweets express do not significantly influence their votes, suggesting that representatives are aware of the potential bias in opinions cascaded in tweets.

History: Gediminas Adomavicius, Senior Editor; Michael Zhang, Associate Editor
Funding: This study was partially funded by Arizona State University Center for Service Leadership, Center for the Study of Economic Liberty, and Dean's Excellence in Research Summer Grants.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/isre.2018.0791.

Keywords: online social media • Twitter • societal impact of IS • U.S. Congress • politics • democratic political system • panel data • difference-in-differences model • sentiment analysis • political ideology

1. Introduction

Online social networking (OSN) platforms have profoundly changed the way we communicate, collaborate, and make decisions. The salient impacts of these platforms on society can be observed in numerous cases. For example, microblogging platforms such as Twitter have been widely credited as key enablers of the Arab Spring, Spain, and Portugal movements in 2011 and the Turkey and Brazil movements in 2013 (Valenzuela 2013, Ghobadi and Clegg 2015, Selander and Jarvenpaa 2016). OSN platforms are known to facilitate users' participation in business (Edvardsson et al. 2011, Goh et al. 2013, Luo et al. 2013, Rishika et al. 2013) and government decision making processes (Bertot et al. 2010, Linders 2012). Furthermore, after President Obama's successful social media campaign during the 2008 presidential election, many politicians explored social media's offerings. For example, several studies consider the role of social media in persuading voters in political campaigns (Wattal et al. 2010, Bond et al. 2012). Although these studies revealed that political candidates can influence voters through social media campaigns, to our knowledge, the influence of voters on politicians has not been studied. That is, politicians use the media to influence voters, but it remains unclear whether voters can influence politicians to vote more in line with voters' wishes during politicians' time in office. Therefore, we aim to study this relationship by focusing on the U.S. House of Representatives.[1]

The wide reach of OSN platforms has convinced many American politicians to be active on these platforms. A 2012 study by Greenberg revealed that nearly

98% of U.S. Representatives had adopted at least one social media platform as a communication and outreach tool (Greenberg 2012). Twitter and Facebook are the most popular OSN platforms among the members of Congress. In the House of Representatives, 75% of members had both Twitter and Facebook accounts as of 2012 (Piper 2013). Moreover, analysis of the post contents by representatives in Greenberg's study revealed that most of them are politically relevant posts. Online social media not only helps lawmakers communicate their messages to constituents, but also gives constituents a channel to interact with their representatives in a convenient way. According to a Congressional Management Foundation report, which was based on a survey of more than 10,000 voters, many believe that "the Internet has become the primary source for learning about and communicating with Congress" (Goldschmidt and Ochreiter 2008, p. 6). According to another report by the Congressional Management Foundation, 42% of the 138 surveyed senior managers, primarily Chiefs of Staff, Deputy Chiefs of Staff and Legislative Directors, and social media managers in Congressional offices consider Twitter an important tool for understanding constituents' views and opinions (Congressional Management Foundation 2011). In a more recent report by the Congressional Management Foundation, 64% of Congressional offices claimed they use social media to gauge public opinion (Fitch and Goldschmidt 2015). Golbeck et al. (2010) analyzed all the tweets that Members of Congress posted during a two-month period and discovered that 7.4% of these tweets were for one-on-one communication with constituents. They maintained, "one benefit that does appear to arise from Members of Congress using Twitter is the potential for increased direct communication with constituents" (Golbeck et al. 2010, p. 1619).

Overall, the adoption and use of online social networks by politicians has the potential to facilitate communication between constituents and representatives. However, it is not clear to what extent the adoption and use of Twitter by representatives truly influences representatives' political decisions and the ways in which representatives deal with the potential biased representation in Twitter users (Mitchell and Hitlin 2013). Our study reveals that the adoption of Twitter by representatives would help representatives align themselves with their constituents' *political ideology* in their voting decisions in Congress. Our results also suggest that this alignment is stronger when the representative's political affiliation differs from that of the constituent. Analysis of the opinions in, and the volume of, tweets directed toward representatives revealed that the volume of tweets (rather than their position) drives this alignment. That is, when Twitter users post a large number of tweets before representatives vote on a bill, they signal the importance of the bill. When representatives vote on such bills, they vote in a manner more aligned with their own constituents' opinions.

This study contributes to the stream of IS research on the societal and political impact of OSNs. These platforms are known for empowering voters and improving transparency, participation, and equality (Chen et al. 2012). However, the primary focus of the extant literature has been on participation and engagement with the new media and less on societal outcomes. In this research, we examine whether the adoption of OSN moves politicians' *voting orientations* closer to the views of their constituents.

The organization of this paper is as follows. Section 2 reviews the relevant literature. Section 3 presents our data, variables, and descriptive statistics. Section 4 discusses the empirical approach. Section 5 reports the results. In Sections 6 and 7, we discuss our findings and conclude with limitations and potential extensions of this study.

2. Research Background

The IS literature has addressed a variety of societal issues, including the digital divide (Riggins and Dewan 2005), e-government services (Carter and Bélanger 2005), political campaigns (Wattal et al. 2010), the prevalence of HIV (Chan and Ghose 2014), the social inclusion of refugees in the host society (Andrade and Doolin 2016), and the well-being of nations (Ganju et al. 2016). All these studies revealed some level of societal impact of IS. To explain the mechanism of impact, Burt (1992) and Wu (2013) proposed that information systems function as enablers for accessing information. Burt (1992) theorized that three distinct informational benefits drive the impact: access, timing, and referrals. Information systems can work as networks hosting useful information and therefore allow users to access more information in a timely manner. Furthermore, users can obtain recommendations from trusted acquaintances. These mechanisms may change users' decisions and, therefore, their performance (Wu 2013). With regard to social media posts, not only the contents, but also the popularity/importance of the contents, as measured by the number of comments, could convey useful information to other users.

Often, information disseminates within a network. A network that provides useful and timely information about voters could help politicians gauge public opinion. This network could allow politicians to seek information from constituents about their opinions and topics/issues that are most important to them. After all, politicians represent their constituents; therefore, understanding constituents' preferences could help politicians make decisions on Capitol Hill. Adam Conner, President Obama's campaign social media strategist, nicely summarizes the role of OSNs: "[Social media puts pressure on governments] almost to the point of removing civil society/NGOs and mainstream media from the debate...[Informing] the great unwashed masses directly is by far the best method to keep both traction and momentum with any policy" (Debating Europe 2013, available at: http://www.debatingeurope.eu/2013/01/22/how-is-social-media-changing-politics/#.Wu8VvS-ZM8Y).

On the other hand, recent studies suggest that although OSNs could give rich information to users, this information could be biased (Ruths and Pfeffer 2014). For instance, a report by Pew Research Center indicates that the Twittersphere is more liberal in reaction to some events and more conservative in reaction to others (Mitchell and Hitlin 2013). Another challenge of OSNs relates to the identification of users. In personal networks, users can identify each other and determine the extent to which they trust the information that others provide. However, in public OSNs such as Twitter, such identification can be challenging. Therefore, the users of OSNs may question the reliability of information cascaded in these platforms.

Given that the first perspective favors the usefulness of OSNs in gauging public opinion and the second perspective casts doubt on this usefulness, we first study the role of OSN adoption by politicians in their *voting orientation* (the extent to which they lean toward liberal or conservative ideologies). Then we extend our study to understand the conditions under which politicians' *voting orientation* becomes more aligned with their constituents after the adoption of Twitter.

3. Data

To study the impact of the adoption of Twitter on the *voting orientation* of politicians, we constructed a panel data for 445 members of the 111th U.S. House of Representatives across a period of 24 months.[2] The 111th U.S. House of Representatives is the ideal entity through which to study the effects of Twitter adoption on representatives' *voting orientation* because many representatives started using Twitter during this period. During the 110th Congress, few representatives adopted Twitter, whereas in the 112th Congress, the adoption of Twitter reached near saturation. The 111th Congress had a more balanced proportion of *adopters/nonadopters* and therefore was more suitable for this study.

3.1. Dependent Variables

Because we are interested in the potential impacts of Twitter adoption on the *voting orientation* of representatives, the first step is to define and estimate a measure of their *voting orientation*. The political science literature has introduced a number of approaches toward measuring the *voting orientation* of representatives based on their roll-call votes. One of the most prevalent methods is the spatial voting model (Clinton 2006). In the spatial voting approach, each representative is assumed to occupy an ideal point in a space of one or more dimensions and each choice presented is a choice between two or more points in that space. Given all the choices (roll-call votes) that representatives made, the spatial model could then estimate a representative's ideal point. Representatives' ideal points in the given space are used to study their *voting orientations*. Traditionally, a two-dimensional space has been used to identify the ideal points of representatives (the first dimension measures the extent to which they are liberal/conservative and the second dimension measures their positions on important polarizing issues such as civil rights). Because in recent years the second dimension has not contributed to the differentiation of representatives based on their votes (that is, the liberal-conservative dimension also differentiates the representatives in terms of current important issues), political scientists have used the first dimension to measure the *voting orientation* of representatives (Clinton 2006, Poole et al. 2011).

Spanning the 111th Congress, we estimate the monthly measure of representatives' *voting orientations* based on votes that each representative cast in a given month. We use weighted nominal three-step estimation (WNOMINATE), a widely used estimation model in political science, for our estimation (Poole et al. 2011).[3] WNOMINATE is a scaling procedure that performs parametric unfolding of binary choice data (Poole and Rosenthal 1985). Given a matrix of binary choices by individuals (i.e., yay or nay) over a series of congressional votes, WNOMINATE produces a configuration of legislators and outcome points for the yay 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 representative and +1 representing the most conservative representative. Political scientists have widely employed WNOMINATE scores to study the behavior of politicians based on their voting records (Aldrich and Battista 2002, Lupu 2013, Aldrich et al. 2014).

Given that the House of Representatives functions on a trustee model of representation,[4] the possibility exists that the representatives would deviate from the views of their constituents and vote based on political party or special interest groups. Therefore, in studying the *voting orientation* of representatives, it is imperative to consider changes in *voting orientation* with respect to constituents' views. From this perspective, we measure the deviation in the *voting orientation* of the representatives and the *political ideology* of the constituents. We call this deviation *political misalignment*. To measure *political misalignment*, we needed a measure for the *political ideology* of the constituents in addition to representatives' *voting orientation*. We obtained such a measure from Tausanovitch and Warshaw (2013). Similar to representatives' *voting orientations*, constituents' *political ideology* measures the extent to which a congressional district leans toward liberal or conservative ideologies. To estimate constituents' *political ideology*, Tausanovitch and Warshaw employ item response theory to scale the policy preferences of respondents to seven recent, large-scale national surveys (the 2006, 2007, 2008, 2010, and 2011 Cooperative Congressional Election Surveys) in all 50 states. Then, they use this large sample to estimate the average policy preferences of voters in every congressional district. They generate estimates of mean policy preferences using multilevel regression with post-stratification. Other empirical studies have used this measure to capture constituents' *political ideology* (Bonica 2014). Because the scale of constituents' *political ideology* is different from that of representatives' *voting orientations*, we normalized both estimates using min-max-scaling such that both estimates range from zero to one, with zero being the most liberal representative/constituent and one being the most conservative representative/constituent. Then, to construct *political misalignment*, we took the absolute difference between the two measures.

3.2. Predictor and Control Variables

To capture the dates on which representatives adopted Twitter, we made API calls to Twitter API and Sunlight Foundation's Congress API, which helped us link representatives' Twitter accounts to their vote data.[5] Out of the 445 representatives, 246 had Twitter accounts by the end of the 111th Congress. Among these 246 representatives, 42 had accounts before the start of the 111th Congress and 204 joined Twitter during the 111th Congress (January 2009–December 2010). Using these data, we constructed a binary Twitter adoption indicator (*Twitter status*) for each representative for a given month. For every month, the value of this binary variable is either 1 if the representative joined Twitter before or during that month or 0 if otherwise. From Twitter,[6] we also collected three additional data sets: First, all the tweets that representatives posted during each month of the 111th Congress. A total of 67,366 tweets were collected from representatives' accounts. Second, all the tweets that mentioned representatives' Twitter handles (official usernames). These data contain 394,389 tweets. Third, all the tweets that mentioned the representatives' names (first name and last name).[7] A total of 1,553,442 tweets were recorded in these data.

Further, we collected data from the Library of Congress (THOMAS), U.S. Census, *NY Times* API, https://voteview.com, the Social Science Research Council (SSRC), and https://www.hubspot.com about the representatives and their constituents. Table 2 provides the descriptions and summary statistics for these variables.

3.3. Descriptive Statistics

Table 1 presents the summary statistics for the data. The mean and standard deviation for representative's *voting orientation* are consistent with prior studies (Poole et al. 2011). The mean of representative's *voting orientation* denotes that the 111th House of Representatives leaned slightly toward the conservative ideology, as it is larger than 0.5. The mean of constituent's *political ideology* denotes that constituents leaned toward the conservative ideology as well.

Political misalignment captures the distance between representative's *voting orientation* and constituent's *political ideology*. The largest possible value for this variable is 1, where the representative is on one end of the political spectrum and the constituent is on the other end. During the 111th Congress, the maximum value for this variable was 0.874. On average, the *political misalignment* was 0.211. Variable *adopter* indicates whether the representative ever adopted Twitter throughout the 111th Congress. The variable *Twitter status* is the representative's *Twitter status* during each month of the study (equals 1 if the representative has a Twitter account at the end of the month and zero otherwise). On average, among all representatives in the House, each representative posted about six tweets during each month and his or her Twitter handle was mentioned about 37 times per month. The remaining variables in Table 1 are instrumental variables that we used to address the selection bias in the adoption of Twitter. We will explain these variables and study their validity in Section 5 and Online Appendix D.

Table 2 reports the summary statistics and descriptions of the control variables.

4. Empirical Methodology

The adoption of Twitter by representatives over time creates a natural experiment setting that allows for a comparison of difference in *voting orientations* before and after Twitter adoption. We exploit the timing variation in joining Twitter across representatives as the basis for identifying the impact of Twitter adoption on *voting orientation*. Numerous research studies have implemented this strategy, including Chan and Ghose (2014), Dranove et al. (2003), Jin and Leslie (2003), and Sun and Zhu (2013). We further address the endogeneity of adoption decision by using instrumental variables, propensity score matching (PSM), and external events, and the serial correlation problem by ignoring the time-series data and randomization inference, as proposed by Bertrand et al. (2004). To assess the effect

Table 1. Summary Statistics of Variables

Variables	Observations	Mean	Standard deviation	Minimum	Maximum
Representative's *voting orientation*	9,320	0.505	0.274	0	1
Constituent's *political ideology*	10,680	0.614	0.184	0	1
Political misalignment	9,320	0.211	0.159	0	0.874
Adopter	10,680	0.553	0.497	0	1
Twitter status	10,680	0.404	0.491	0	1
Tweets frequency	10,680	6.308	17.589	0	385
Handle_mentions frequency	10,680	36.928	124.776	0	1,637
Instrumental variables					
Name_mentions frequency	10,632	146.110	226.021	0	1,923
Committee effect	10,680	0.388	0.153	0	1
Neighbor effect	10,680	0.363	0.186	0	0.875
Caucus effect	10,680	0.344	0.180	0	0.765

Notes. For August 2009 and August 2010, the WNOMINATE scores were not estimated because the House of Representatives was in recess. We also excluded representatives who voted on fewer than 20 bills during any given month (please refer to Online Appendix B). *Tweets frequency* is the number of tweets posted by the representatives during any given month. *Handle_mentions frequency* is the number of tweets in which the representatives' Twitter handles were mentioned on Twitter in any given month excluding their tweets about themselves. *Name_mentions frequency* is the number of tweets in which the representatives' first name and last name were mentioned on Twitter in any given month excluding their tweets about themselves. Tweets that contained both handle and name were counted in each category. For more information, please refer to Online Appendix C.

of Twitter adoption on representatives' *voting orientation*, we employ the following model:

$$y_{it} = \beta x_{it} + \alpha Z_i + \theta T_t + u_{it}, \tag{1}$$

where i is the index for representatives and t is the index for time, t = January 2009, February 2009,..., December 2010 (excluding August 2009 and August 2010); x_{it} (*Twitter status*) is the binary variable for adopting Twitter, meaning x_{it}=1 if the representative has a Twitter account at time t and zero if otherwise. Z_i is the representative's fixed effects. We also include time fixed effects for each month (T_t) from January 2009 to December 2010 to control for changes in representatives' average propensity to vote in favor of liberal or conservative

Table 2. Summary Statistics and Descriptions for Control Variables

Variable	Description	Source	Observations	Mean	Standard deviation	Minimum	Maximum
Age	Representative's age	THOMAS	10,680	57.164	10.293	28	86
Gender	Representative's gender (1 if male)	THOMAS	10,680	0.829	0.376	0	1
Seniority	The number of years the representative has been in the body (House or Senate) of which he or she is currently a member	Sunlight API	10,680	11.935	9.130	1	56
Party vote	The percentage of votes in which the representative's position agreed with the party's majority position	Sunlight API	10,680	94.12	4.369	70.83	99.09
Sponsorship	The number of bills sponsored by the representative while in that particular role	*NY Times*	10,680	18.997	13.348	0	84
Cosponsorship	The number of bills cosponsored by the representative while in that particular role	*NY Times*	10,680	339.691	144.759	0	966
Missed votes	The percentage of votes in which the representative was eligible to vote but did not	Sunlight API	10,680	4.693	6.990	0	93.4
Household income	Mean logarithm household income in representative's district	U.S. Census	10,680	10.827	0.252	10.084	11.532
High school graduate	% of high school graduates in the representative's district	SSRC	10,680	85.028	6.761	55.1	96.2
White	% of white population in the representative's district	SSRC	10,680	76.529	17.667	16.04	98.12

initiatives. u_{it} is the error term. We use specification 1 to study the impact of representatives' adoption of Twitter on two dependent variables (y_{it}). For the first dependent variable, we use representatives' *voting orientations* (normalized WNOMINATE). In this case, β is our difference-in-differences estimator that captures the effect of Twitter adoption on representatives' *voting orientation*. A positive and significant value for β means the representatives became more conservative after adopting Twitter, while a negative and significant value for β means the representatives became more liberal after the adoption. For the second dependent variable, we use *political misalignment*. A decrease in *political misalignment* means the representatives became more aligned with the constituent in terms of *voting orientation*. An increase in *political misalignment* means that the representatives became less aligned with the constituent in terms of *voting orientation*. In this case, β is our difference-in-differences estimator that captures adoption's effect on *political misalignment* between the representatives and their constituents. A positive and significant value for β means the representatives became less aligned with their constituents after adoption, while a negative and significant value for β means the representatives became more aligned with their constituents after adoption.

5. Results

For model-free evidence, Table 3 provides a comparison of *adopters* and *nonadopters* before and after their adoption of Twitter. Compared to *nonadopters*, eventual *adopters* had a much lower mean *voting orientation* before they adopted Twitter (0.386 vs. 0.484). This means representatives who adopted during the 111th Congress, were more liberal than their *nonadopter* peers. However, after adoption, the *adopters* had a higher mean *voting orientation*. That is, *adopters* became more conservative after joining Twitter.

Table 3 also shows that the constituents of representatives who adopted Twitter during the 111th Congress had a mean *voting orientation* of 0.606. The constituents of representatives who did not adopt Twitter during the 111th Congress had a slightly higher mean *voting orientation* (0.624). The *political misalignment* between *nonadopter* representatives and their districts is 0.231 throughout the 111th Congress. Among the *adopter* districts, *political misalignment* becomes 14.1% smaller after adoption. One possible explanation for this observation could be that we measured the changes in the *adopters' voting orientation* and *political misalignment* over time (the mean before and the mean after the adoption), whereas for *nonadopters* we used the mean over the entire period of the 111th Congress. That is, it is possible that the *adopters* and *nonadopters* behaved similarly throughout the 111th Congress, but we caught the *adopters* in motion. However, our results reported in Table 6 will provide further evidence that *adopters* and *nonadopters* indeed behave differently even after we take into account of changes in their voting behaviors over time.

Table 4 reports our estimation results. Model 1 reports the results based on the fixed effects specification without the instrumental variables. The fixed effects control for observed and unobserved time invariants, such as age, gender, longevity of service, and constituents' characteristics across the representatives. The coefficient for *Twitter status*, which reflects the average effect of adoption on the *adopter* group, is significant and positive. According to Model 1, *adopters' voting orientation* increases by 2.2 percentage points after adoption.

Representatives' decision to adopt Twitter can be correlated with their *voting orientation*. For instance, those representatives who decide to become more aligned with their constituents could also decide to adopt Twitter as a new communication channel with them. Therefore, the decision to adopt Twitter (or the selection to be in the treatment or control group) could be endogenous to representatives' *voting orientation*. Although fixed effects are useful in controlling for time-invariant unobservables, they do not control for time-variant unobservables that may correlate with the decision to adopt Twitter. These time-variant unobservables could lead, for example, to different trends over time for *adopters* and *nonadopters*. One way to address this issue would be to employ time-variant instrumental variables. We construct four time-variant instrumental variables to account for the effects of time-variant unobservables. Valid instruments must correlate with the decision to adopt but affect the dependent variable only through the adoption decision. We construct the first instrumental variable (*name-mentions frequency*) by counting the number of tweets in which the representatives' first names and last names were mentioned on the Twittersphere in any given month. The representatives cannot control whether they are mentioned by first name and last name. That is, every Twitter user can mention the representatives even

Table 3. Comparison of Means Between Eventual *Adopters* and *Nonadopters*

Variable	Period	*Adopter*	*Nonadopter*
Representatives' voting orientation	Before adoption (*Twitter status* = 0)	0.386	0.484
	After adoption (*Twitter status* = 1)	0.572	
Constituents' voting orientation	Throughout the 111th Congress	0.606	0.624
Political misalignment	Before adoption (*Twitter status* = 0)	0.238	0.231
	After adoption (*Twitter status* = 1)	0.179	

Table 4. Impact of Twitter on *Voting Orientation* and *Political Misalignment* (Adoption of Twitter)

	DV = *voting orientation*				DV = *political misalignment*			
	Model 1	Model 2	Model 3		Model 4	Model 5	Model 6	
			Coefficient	Marginal effect			Coefficient	Marginal effect
Twitter status	(0.022*** [0.006])	(0.097*** [0.013])	(0.099*** [0.025])	(0.018*** [0.005])	(−0.010* [0.004])	(−0.041*** [0.014])	(−0.093*** [0.029])	(−0.014*** [0.004])
Controls			✓				✓	
Robust	✓		✓		✓		✓	
Time fixed effects	✓	✓	✓		✓	✓	✓	
Representative fixed effects	✓	✓	✓		✓	✓	✓	
Time interaction with treated and controlled		✓				✓		
Instruments		✓				✓		
Within *R*-squared	0.491	0.474			0.228	0.224		
N	9,320	9,276	9,320		9,320	9,276	9,320	
F-statistic	472.27	234,402.09	35,090.31		115.61	40,988.43	10,933.51	
Prob > *F*	<0.001	<0.001	<0.001		<0.001	<0.001	<0.001	
Specification	FE	FE/2SLS	ZOIB		FE	FE/2SLS	ZOIB	

Notes. We used Eicker-Huber-White robust standard errors. Within-panel *R*-squared is reported in FE models. First-stage estimates for instrumental variables are reported in Online Appendix D. Wald's chi-square test is reported for ZOIB models instead of *F*-statistic. In ZOIB models, the size of the coefficient is not interpretable. Therefore, marginal effects are reported and should be used for interpretation. Marginal effects for *Twitter status* represent the percentage point changes in the proportions by shifting from the control group to the treatment group.
$^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

if those representatives have not created a Twitter account. We believe that those representatives who are mentioned frequently are more likely to have created an account and to use this channel to communicate with voters. Therefore, we argue that the number of representatives' name-mentions in the Twittersphere is a good choice of instrument. According to Table 1, representatives' names were mentioned 146 times per month on average.

The second instrument (*committee effect*) is created by dividing the count of the representative's cocommittee peers who had adopted Twitter by the end of each time period *t* by the total count of committee peers in all the committees of which the representative is a member. The rationale is that the choice to use Twitter among representatives from the same committees may be correlated. That is, if more representatives whom the representative knows (and with whom the representative regularly interacts during committee meetings) adopt Twitter, the representative may be more inclined to adopt it as well. The value of this instrumental variable ranges from 0 to 1 with a mean of 0.388. We constructed the third instrument (*neighbor effect*) by counting the proportion of peers from the representative's state who had adopted Twitter by the end of each time period t. Again, the idea is that the choice to adopt Twitter among representatives from the same state may be correlated (Golbeck et al. 2010, Peterson 2012).[8] Finally, we used caucus memberships as the source of data for the fourth instrument, *caucus effect*. In general, a representative could be a member of several informal organizations while in service in Congress. These informal organizations are called informal member organizations and can be divided into two groups: (1) Congressional Member Organizations (CMO or caucus), which are registered with the Committee on House Administration, and (2) informal member groups (IMG), which are not registered anywhere. Among the two, CMOs are longer lasting than IMGs and are also governed by House rules (Glassman 2017). Therefore, we focused only on CMOs to measure the *caucus effect*. We obtained the list of all CMOs and their members from Victor (2013) and used the same approach we used in *committee effect* to measure *caucus effect*. These four instrumental variables were used in Models 2 and 5 in Table 4.

Model 2 reports the results of the fixed effects model using four instrumental variables with the 2SLS specification. The coefficient for *Twitter status* is, again, significant and positive, indicating that *adopters' voting orientation* shifts toward the conservative end of the spectrum by 9.7 percentage points after adoption.

Model 3 reports the results with the zero-one inflated beta distribution (ZOIB) specification. The reason for the use of this specification is that both *voting orientation* and *political misalignment*'s range of values is bounded. That is, *voting orientation* and *political misalignment* are allowed to vary only from 0 to +1. Because the ordinary least squares (OLS) specification assumes a normal distribution, the linear specification may not work well in this setting. Kieschnick and McCullough (2003) recommend parametric regression models based on beta distribution for such data. The ZOIB model also has been widely adopted in political science literature when WNOMINATE scores were employed to construct the outcome variable (Burmester and Jankowski 2014). For Model 3 in Table 4, both the coefficients and their marginal effects are provided. The coefficient for *Twitter status* is significant and positive, indicating the representatives become 1.8 percentage points more conservative according to the marginal effect in Model 3.

The outcome variable in Models 4–6 is *political misalignment*. The coefficient for *Twitter status* is negative and significant in all three models. Although the magnitude of impact is not large according to the estimates in Models 4 and 6 (1 percentage point and 1.4 percentage points, respectively), the magnitude of the impact is larger when we use the instrumental variables (Model 5). According to this result, representatives who adopted Twitter during the 111th Congress became more aligned with their constituents. Given that the mean *political misalignment* is 0.211 (Table 1), a change of 0.041 point corresponds to approximately 20% more alignment. These findings still hold even if we use the square of *political misalignment*, as reported in Online Appendix E.

We used Eicker-Huber-White robust standard errors in Models 1, 3, 4, and 6. We also include time fixed effects for each month from January 2009 to December 2010 to control for changes in overall shifts in representatives' *voting orientation*. All models include the representative fixed effects. To check the robustness of our findings, we removed those representatives who adopted Twitter before January 2009, then replicated our analysis for the new sample. The results were similar to the results reported in Table 4. We also allow for the time interaction with treated and controlled groups in Models 2 and 5.

Next, we examine the effect of Twitter use on the representatives' *voting orientation* and *political misalignment*. Because the use of Twitter by *adopters* could be heterogeneous (for instance, some of the representatives may not actively use Twitter after they create accounts), as an indicator for use, we calculate the log number of tweets that representatives posted each month (*tweets frequency*).[9] To study the relationship between Twitter use and *voting orientation* and *political misalignment*, we run two models with the FE specification. According to Table 5, the coefficient for *tweets frequency* is positive and significant in Model 7 and negative and significant in Model 8. These results further support our initial findings about the role of Twitter in *voting orientation* and *political misalignment*. That is, the frequency of tweets that representatives post is associated with more conservatism and lower *political misalignment* with constituents.

As an indicator of constituents' use of Twitter, we used the log of number of tweets that mentioned representatives' Twitter handles (*handle_mentions frequency*) in any given month.[10] According to the results reported in Online Appendix F, representatives who are mentioned more frequently on the Twittersphere tend to be more aligned with their constituents.

5.1. Addressing the Selection Bias

Given that the instrumental variables approach we have undertaken to address the selection problem relies on the instruments' validity, and that we are unable to empirically test the exogeneity of the instrumental variables, in the following section we employ a variety of methods to address the selection bias.

5.1.1. PSM. One of the methods for evaluating potential selection effects is the PSM approach (DiPrete and Gangl 2004, Sun and Zhu 2013, Leuven and Sianesi 2014). The instrumental variable approach and the PSM approach rely on different sets of assumptions. The instrumental variable approach relies on exogenous variables to purge the effects of unobservables on the decision to adopt. In PSM, the idea is to compare

Table 5. Impact of Twitter on *Voting Orientation* and *Political Misalignment* (*Frequency of Tweets*)

	DV = *voting orientation* (Model 7)	DV = *political misalignment* (Model 8)
Tweets frequency (logged)	0.010*	−0.006*
	(0.004)	(0.002)
Robust	✓	✓
Time-fixed effects	✓	✓
Representative fixed effects	✓	✓
R-squared (within)	0.471	0.198
N	9,320	9,320
F-statistic	287.78	79.89
Prob > *F*	<0.001	<0.001
Specification	FE	FE

Note. We used Eicker-Huber-White robust standard errors.
$^*p < 0.05$.

representatives who, based on observables, have a very similar probability of receiving treatment (i.e., a similar propensity score), except that one of them received the treatment and the other did not. Under the PSM scheme, as attributes to be matched upon, we used the representative's age, gender, seniority in Congress, percentage of party-favored votes, number of sponsored bills, number of cosponsored bills, percentage of missed votes, constituents' mean household income, percentage of high school graduates, and percentage of white population. Table 2 provides the descriptions and summary statistics for these variables.

Because the PSM method requires one pre-event and one post-event observation for each subject, and because representatives created their Twitter accounts over time, we first collapse each of our outcome variables, y_{it} into simple averages before and after time t for each representative, and denote these averages as y_i^{pre} *and* y_i^{post}. Because we are interested in the difference-in-differences model, the target variables will be the changes ($\Delta y_i = y_i^{post} - y_i^{pre}$) in *voting orientation* and *political misalignment*. We compare the average treatment effect of representatives whose *Twitter status* is 1 with a representative whose *Twitter status* is 0 but within the common support region.

We run our models in three different settings: Setting 1 compares *adopters* and *nonadopters* in a yearly format; Setting 2 compares *adopters* and *not-yet adopters* (those who did not adopt during time *t* but who will do so before the end of the 111th Congress) in a yearly format; and Setting 3 compares *adopters* and *not-yet adopters* in a monthly format.[11]

Setting 1. We broke the 24-month period into two periods: (1) year 2009 and (2) year 2010. The variables *voting orientation* and *political misalignment* were averaged for each representative for each year. The variable *Twitter status* is equal to 1 if the representative has an active Twitter account during at least part of the time period (year) and zero if otherwise.

Setting 2. Similar to Setting 1, we broke the 24-month period into two periods: (1) year 2009 and (2) year 2010. The only difference between Settings 1 and 2 is that, in Setting 1, we included *nonadopters* (those who never adopted during the 111th Congress) in the control group, while we excluded them in Setting 2. Table 6 reports the results of our analysis (the average treatment effect on the treated) for Settings 1 and 2.

According to Table 6, the difference-in-differences coefficient is positive and significant in both settings when the target variable (Δy_i) is the changes in *voting orientation* and is negative and significant when it is the changes in *political misalignment*. These findings are similar to our previous findings.

Setting 3. This setting is similar to Setting 2, with only the difference being that the time period *t* is each month[12] rather than each year. Figure 1 shows the number of *adopters* during each calendar month.

Twitter status estimates in Model 11 remain positive and statistically significant for every month except for March 2009. The impact of Twitter adoption on changes in *voting orientation* ranges from 0.022 points to 0.047 points. The impact of Twitter adoption on changes in *political misalignment* remains negative and significant for every month except March and June 2009. The impact of Twitter adoption on changes in *political misalignment* ranges from −0.082 to 0.031. With a few exceptions, the results of PSM analysis confirm our previous findings.

5.1.2. External Events. Besides using instrumental variables and PSM techniques, we further address the potential endogeneity of Twitter adoption by leveraging an external event that was known for driving Twitter adoption. On May 19, 2010, Twitter launched Twitter for iPhone and iPod for free on the iTunes App Store (Stone 2010). Given the fact that iPhone was the most popular mobile device among the members of Congress, as it was claimed that over 71% of them use the iPhone (Hattem 2014),[13] we believe this external event may have motivated some of the representatives to start using Twitter. In particular, June 2010 had the highest number of *adopters* in the second half of the Congress, and the decision to create a social media account due to the app's availability for mobile devices is unlikely to be correlated with the changes in representatives' *voting orientation*. We thus narrow down the sample to only those who created their Twitter accounts during the month of June 2010 for a robustness check. Table 8 reports our estimation results for representatives who adopted Twitter in June 2010 and representatives who never adopted. According to the results in Table 8, the coefficient for *Twitter status* is significant and positive for *voting orientation* and significant and negative for *political misalignment*, confirming our previous findings.

5.1.3. Twitter Usage and *Political Misalignment.* If, indeed, the adoption of Twitter by representatives influences their decisions in favor of their constituents, it is expected that the magnitude of this influence will be larger in geographic regions where people use Twitter more often. Therefore, we collected data about per capita usage of Twitter per state[14] to compare the influence of Twitter adoption on *political misalignment* across states. Among the 50 states, Mississippi had the lowest per capita Twitter usage score. Massachusetts had the highest per capita Twitter usage score. Because these data are at the state level, we averaged the district level *political misalignment*s for each state and then ran a

Table 6. Difference-in-Differences Estimates for Settings 1 and 2 (Yearly)

	Including never *adopters* (Setting 1, Model 9)	Excluding never *adopters* (Setting 2, Model 10)
Political orientation	0.080***	0.155***
	(0.020)	(0.041)
Political misalignment	–0.034***	–0.037*
	(0.009)	(0.018)

Note. AI robust standard errors are reported in parentheses. A logit model was used for estimations. One nearest neighbor was matched. $^{**}p < 0.01$; $^{***}p < 0.001$.

regression model with state-level *political misalignment* as the dependent variable and Twitter usage and control variables[15] as the regressors. The coefficient for Twitter usage was –0.039 ($p < 0.001$), revealing that *political misalignment* is smaller in states where Twitter is used more often. This finding confirms our prior findings about the role Twitter adoption plays in *political misalignment*.

5.2. Addressing the Bias Due to Serial Correlation

Because this study's difference-in-differences coefficients rely on many months of data and focus on serially correlated outcomes, the estimated standard errors may be serially correlated. This is especially problematic because the adoption of Twitter across representatives is itself serially correlated, which will exacerbate the bias in standard errors. To address this problem, we employ the following methods:

5.2.1. Ignoring Time-Series Information. Bertrand et al. (2004) notes that collapsing the time-series information into a "pre-" and "post-" period produces consistent standard errors and is an effective correction for inconsistent standard errors due to serially correlated outcomes. To construct collapsed *voting orientation*, we calculate the representative's simple average *voting orientation* before adoption (y_i^{pre}) and after adoption (y_i^{post}). Similarly, we obtain the value of *political misalignment* before adoption (y_i^{pre}) and after adoption (y_i^{post}) by taking the simple average of *political misalignment* before and after adoption. According to Table 9, the results in both models confirm our previous findings. The impact of Twitter adoption on mean *voting orientation* is positive and significant (a 0.071-point increase in mean *voting orientation*), whereas its impact on mean *political misalignment* is negative and significant (a 0.039-point decrease in misalignment).

5.2.2. Randomization Inference. Another way to address serial correlation is to employ a randomization inference method (Bertrand et al. 2004). In this approach, computing the standard error for a specific experiment takes a two-step approach. First, the difference-in-differences estimates for a large number of randomly generated placebo laws are estimated. Then the empirical

Figure 1. Frequency of *Adopters* During Each Calendar Month

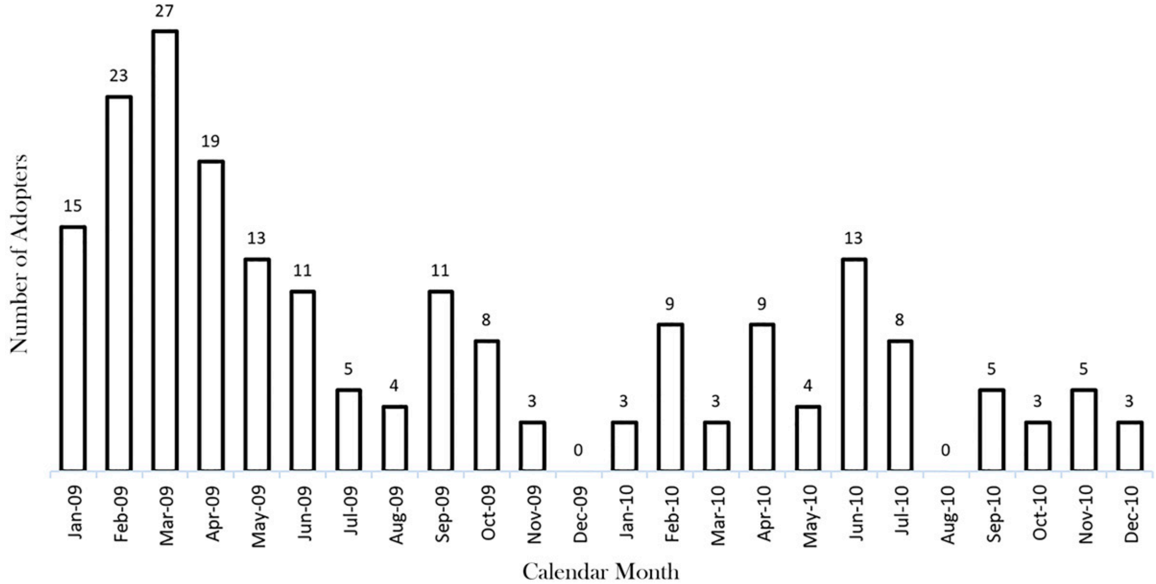


Table 7. Difference-in-Differences Estimates for Setting 3 (Monthly)

Calendar month	Model 11 (Δy_i = Changes in *voting orientation*)	Model 12 (Δy_i = Changes in *political misalignment*)	Number of *adopters*
Feb. 2009	0.043**	−0.026***	23
	(0.016)	(0.005)	
Mar. 2009	0.024	0.031**	27
	(0.18)	(0.010)	
Apr. 2009	0.022*	−0.029***	19
	(0.013)	(0.008)	
May 2009	0.026*	−0.015*	13
	(0.011)	(0.007)	
Jun. 2009	0.032**	0.056	11
	(0.011)	(0.067)	
Sep. 2009	0.047**	−0.082***	11
	(0.013)	(0.022)	
Jun. 2010	0.027*	−0.051***	13
	(0.010)	(0.015)	

Notes. AI robust standard errors are reported in parentheses. A logit model was used for the estimations.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

distribution of the estimated effects for these placebo laws is used to form a significance test for the true law. In our case, we started by estimating the difference-in-differences estimate (β in specification 1) using the observed data. The next step is to generate the placebo data randomly many times and to run the model in specification 1 on this placebo data. We created 10,000 placebo data sets. To create each placebo data, we randomly drew 204 representatives[16] from among all the representatives in our data and allowed each of them to randomly choose a month to adopt Twitter. We then ran a model with specification 1 on this placebo data and obtained the difference-in-differences coefficient. Repeating this procedure 10,000 times results in 10,000 difference-in-differences estimates. The next step is to compare the actual difference-in-differences estimate in the first

Table 8. Impact of Twitter on *Voting Orientation* and *Political Misalignment* (June 2010 *Adopters*)

	DV = *voting orientation*				DV = *political misalignment*			
	Model 13	Model 14	Model 15		Model 16	Model 17	Model 18	
			Coefficient	Marginal effect			Coefficient	Marginal effect
Twitter status	0.062***	0.293***	0.273***	0.051***	−0.024*	−0.125***	−0.186*	−0.029*
	(0.013)	(0.028)	(0.070)	(0.013)	(0.009)	(0.029)	(0.088)	(0.013)
Controls			✓				✓	
Robust	✓		✓		✓		✓	
Time fixed effects	✓	✓	✓		✓	✓	✓	
Representative fixed effects	✓	✓	✓		✓	✓	✓	
Time interaction with treated and controlled		✓				✓		
Instruments		✓				✓		
Within R-squared	0.535	0.537			0.300	0.304		
N	4,420	4,398[a]	4,420		4,420	4,398	4,420	
F-statistic	207.67	107,217.50	16,135.22		77.46	23,961.20	6,157.60	
Prob > F	<0.001	<0.001	<0.001		<0.001	<0.001	<0.001	
Specification	FE	FE/2SLS	ZOIB		FE	FE/2SLS	ZOIB	

Notes. We used Eicker-Huber-White robust standard errors. Within-panel R-squared is reported in FE models. Wald's chi-square test is reported for ZOIB models instead of an F-statistic. In ZOIB models, the size of the coefficient is not interpretable. Therefore, marginal effects are reported and should be used for interpretation. Marginal effects for *Twitter status* represent the percentage point changes in the proportions by shifting from the control group to the treatment group.

[a]Rep. Mike Rogers (MI 8th) adopted Twitter in June 2010. As noted as noted in endnote 7, because of the similarity between his first and last name with Rep. Mike Rogers (AL 3rd), we could not obtain his *name_mentions frequency* and therefore eliminated him from the FE/ 2SLS analysis. However, we ran FEs/2SLS models in which we only used *committee effect*, *caucus effect*, and *neighbor effect* (without the instrumental variable *name-mentions frequency*). The estimate in Model 14 was 0.296*** and −0.132*** in Model 17.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 9. Impact of Twitter on *Mean Voting Orientation* and *Mean Political Misalignment*

	DV = *mean voting orientation* (Model 19)	DV = *mean political misalignment* (Model 20)
Twitter status	0.071***	-0.039***
	(<0.001)	(<0.001)
Robust	✓	✓
R-squared (within)	0.449	0.207
N	10,537	10,537
F-statistic	331.11	106.57
Prob > *F*	<0.001	<0.001
Specification	FE	FE

Note. We used Eicker-Huber-White robust standard errors.
***$p < 0.001$.

step with the distribution of the placebo estimates. We set the significance level at 0.05. To form a two-tailed test of level 0.05, we identified the placebo difference-in-differences estimates at the 0.025 lower and upper tail of the distribution and used these values as cutoffs. If the actual difference-in-differences estimate lies outside these two cutoff values, we rejected the hypothesis that it was equal to 0; otherwise, we accepted it. Table 10 reports the results of this procedure for both *voting orientation* and *political misalignment*.

Table 10 shows that both actual difference-in-differences estimates for *voting orientation* and *political misalignment* lay outside the 95% distribution of the placebo estimates. For *voting orientation*, the actual difference-in-differences estimate is higher than the upper bound. That is, the effect of adoption on *voting orientation* is positive and significant at 0.05. For *political misalignment*, the actual difference-in-difference estimate is lower than the lower bound. That is, the effect of adoption on *political misalignment* is negative and significant at 0.05. The results in Table 10 confirm the previous results about the effects of Twitter adoption on *voting orientation* and *political misalignment*.

5.3. Representative-Specific and Constituent-Specific Effects

To elaborate further on the effect of Twitter adoption on representatives' *voting orientation* and *political misalignment*, we introduced the representative-specific and constituent-specific factors as moderators to our model in specification 1, resulting in specification 2:

$$y_{it} = \beta x_{it} \times F_i + \alpha Z_i + \theta T_t + u_{it}, \tag{2}$$

where F_i is a representative-specific or constituent-specific factor. Table 11 summarizes the effects of these factors on the relationship between Twitter adoption and *voting orientation* and *political misalignment*. The most interesting finding is the effect of representative-constituent *party match*. representative-constituent *party match* takes the value of 1 if the representative's party affiliation matches the constituent's party affiliation, and 0 if otherwise. Table 11 shows that those representatives who represent an opposing party's district get closer to their constituents after the adoption of Twitter. Their *political misalignment* reduces about 2.6 times more than that of the other representatives whose party affiliation matches their constituents' party affiliation. In other words, a Republican representative elected in a Democrat district or a Democrat representative elected in a Republican district reduce misalignment with their constituents more so after Twitter adoption than do representatives who represent their own party districts. The reason for this observation could be that these representatives feel more pressured by their constituents and are thus more sensitive to their Twitter activities. Table 11 also shows that, after joining Twitter, Democrat representatives' *voting orientation* scores increase more than those of their Republican peers. Democrats also

Table 10. Randomization Inference Results with 10,000 Simulations

	DV = *voting orientation*			DV = *political misalignment*		
	Actual estimate	Lower bound estimate	Upper bound estimate	Actual estimate	Lower bound estimate	Upper bound estimate
Twitter status	0.022	−0.012	0.012	−0.010	−0.009	0.010
Time fixed effects	✓	✓	✓	✓	✓	✓
Representative-specific effects	✓	✓	✓	✓	✓	✓
Specification	OLS	OLS	OLS	OLS	OLS	OLS

Table 11. The Effects of Moderating Factors on *Voting Orientation* and *Political Misalignment*

	Adoption effect on *voting orientation*	Adoption effect on *political misalignment*
Representative and constituent party match = 1	N	+
Party affiliation = Republican	−	+
Age	N	N
Seniority	N	N
Sponsorship	N	N
Cosponsorship	+	N
Missed votes (%)	N	N
Party votes (%)	+	−
White (%)	−	N
High school graduates (%)	−	N
Household income (logged)	−	+
Unemployment rate (%)	+	N

Notes. FEs specifications are used in all of the models. We interacted each factor with *Twitter status* in specification 1. N means no significant effect, + and − are the sign of the coefficient for the interaction term. + for *voting orientation* means that the representative became more conservative; for *political misalignment* it means that the representative further deviated from the constituent. − for *voting orientation* means that the representative became less conservative; for *political misalignment* it means that the representative became more aligned with the constituent. Almost in 18% of the districts the affiliation of the representative was different from constituent. Overall, 41% of the representatives were Republican. Descriptions and summary statistics of other variables are provided in Table 2.

become closer to their constituents, as they join Twitter more than Republicans do. Another interesting finding in Table 11 relates to the effect of *party votes*, which is the percentage of votes in which the representative's position agreed with the party's majority position. Representatives with a higher score on *party vote* (those who used to vote along party lines) are more likely to adjust their voting decisions after adoption.

5.4. Understanding the Underlying Mechanisms

Our analysis so far offers evidence that representatives' adoption of Twitter may influence their *voting orientation* and their *political misalignment* with constituents. The dependent variables in our models (*voting orientation* and *political misalignment*) are measures of leaning toward the liberal or conservative ends of the spectrum. The dependent variable *voting orientation* is based on many roll-call votes on a variety of bills. The dependent variable *political misalignment* is also based on those bills as well as on many topics on which constitutions have an opinion. Another way to study the effect of adoption would be to focus on single topics and examine how adoption could change representatives' positions on those topics. For each selected topic, we must define a measure for the representative and a measure for the constituent. We can also observe and quantify the information that Twitter users shared with respect to those topics. To perform this type of analysis, we decided to focus on the issue of abortion.[17] Our intention in this section is to examine the potential effects of representatives' Twitter adoption on their votes on abortion-related bills, given their district's abortion preference and abortion-related content that users shared close to the time of voting.

To collect the votes cast on abortion-related bills, we collected data from Sunlight Foundation's Congress API using a homebrew Python code. The Congress API would allow us to search for bills in Congress. We used "abortion" as the search term to obtain all bills related to abortion during the 111th Congress.[18] The search returned 48 entries. Because we needed the representatives' votes on those bills, we kept only those that were voted on in the House floor during the 111th Congress. This reduced our list to 11 bills (Table 12).

We divided the bills into five groups, and assigned a score to each group: strongly prochoice bills (score: +2), somewhat prochoice bills (score: +1), neither prochoice nor prolife bills (score: 0),[19] somewhat prolife bills (score: −1), and strongly prolife bills (score: −2). We then removed all the bills with a score of zero (HR20, HR2847, and HR3081). There were three possible outcomes regarding representatives' *voting orientation* on the bills: vote yay (+1), vote nay (−1), and not voting or vote present (0). For each representative and bill *j*, we multiplied the group score by the representative's vote to construct what we call the representative's *prochoice score*. If there was more than one vote within a single month, the votes were averaged so that there was only one score for each month.

We used the following specification to examine the potential effect of Twitter adoption on a representative's vote on abortion bills.

$$y_{it} = \beta_1 x_{it} + \beta_2 x_{it} \times CD_i + \alpha Z_i + \theta T_t + u_{it}, \qquad (3)$$

where i is the index for representatives and t is the index for time, t = March 2009, June 2009, July 2009, December 2009, March 2010, and June 2010 (each month during which there was a vote on abortion bills); y_{it} is the representative's *prochoice score* at time t, Z_i is the representative's fixed effects, x_{it} is the representative's *Twitter status* at time t (1 if active on Twitter), and CD_i is the *prochoice score* for the congressional district

Table 12. List of Abortion Bills Voted on in the House Floor During the 111th Congress

Bill	Brief description	Vote date	Bill score
HR1105	Making omnibus appropriations for the fiscal year ending September 30, 2009, and for other purposes	Mar. 10, 2009	+1
HR20	To provide for research on, and services for individuals with, postpartum depression and psychosis	Mar. 30, 2009	0
HR1388	The Edward M. Kennedy Serve America Act, an Act to reauthorize and reform the national service laws	Mar. 31, 2009	−1
HRES505	Condemning the murder of Dr. George Tiller, who was shot to death at his church on May 31, 2009	Jun. 9, 2009	+2
HR3170	Making appropriations for financial services and general government for the fiscal year ending September 30, 2010, and for other purposes	Jul. 16, 2009	+2
HR3293	Making appropriations for the Departments of Labor, Health and Human Services, and Education, and related agencies for the fiscal year	Jul. 24, 2009	+1
HR3962 (Amendment 509)	Amendment to Preservation of Access to Care for Medicare Beneficiaries and Pension Relief Act of 2010	Nov. 7, 2009	−2
HR3288	Making appropriations for the Departments of Transportation, and Housing and Urban Development, and related agencies for the fiscal year	Dec. 13, 2009	+1
HR2847	Making appropriations for the Departments of Commerce and Justice, and Science, and Related Agencies for the fiscal year	Dec. 17, 2009	0
HR3590	An act entitled The Patient Protection and Affordable Care Act	Mar. 22, 2010	+2
HR3081	Making continuing appropriations for fiscal year 2011, and for other purposes	Sept. 30, 2010	0

that the representative serves. To measure the *prochoice score* for each congressional district (CD_i), we used the data and script from Warshaw and Rodden's (2012) companion website. Warshaw and Rodden developed and used a multilevel regression and post-stratification (MRP) model that combines survey and census data to estimate public opinion against abortion at the district level. The original estimations range from 0.079 (CA 8th district) to 0.646 (KY 5th district) with a mean of 0.403. Because we were measuring the *prochoice score*, we multiplied the original scores by −1 and then standardized it to have a mean of 0 and standard deviation of 1. We call this variable district's *prochoice score*, which ranges from −2.548 (the least prochoice district) to 3.378 (the most prochoice district).

We used specification 3 to run the models eight times. The first four times, we included bill HRES505, which was about condemning the shooting of abortion doctor and prochoice activist Dr. George Tiller. In the next four runs, we excluded this bill from the data and replicated the estimations. We did this because HRES505 was not a policy bill. That is, a representative might be very prolife but still condemn the shooting of Dr. Tiller. Given the distribution of the dependent variable, we also used the fractional logit model (Williams 2016) after transforming the representative's *prochoice score* to range from 0 to 1. Table 13 presents the results.

The results in Table 13 suggest that a representative's adoption of Twitter would impact the representative's *voting orientation* on abortion. The coefficient for *Twitter status* is positive and significant in all models, except Model 24. Another interesting relationship between representatives' Twitter adoption and *voting orientation* unfolds when we study the interaction term between *Twitter status* and district's *prochoice score*. According to specification 2, the partial derivative of y_{it} with respect to x_{it} (assuming that CD_i and u_{it} are independent of x_{it}) will be $\partial y_{it}/\partial x_{it} = \beta_1 + \beta_2 \times CD_i$. For instance, in Model 26, the partial derivative will be $0.245 + (0.683 \times CD_i)$. Because CD_i could range from −2.548 to 3.378, the effect of adoption on the representative's prochoice *voting orientation* depends on the value of district i's *prochoice score*. If the district's score is close to −0.359, the adoption has no effect on the representative's prochoice *voting orientation*. If the district's score is greater than −0.359, the adoption has a positive effect on the representative's prochoice *voting orientation*. If the district's score is less than −0.359, the adoption has a negative effect on the representative's prochoice *voting orientation*. This means if the district has a significantly positive or significantly negative opinion about abortion, the representative would align with that opinion after adoption. On the other hand, if the district does not have a distinct prochoice or prolife opinion about abortion, adoption does not have a large impact.

This finding sheds more light on the effects of representatives' social media adoption on their *voting orientation*. Although there was a prochoice trend in representatives' prochoice *voting orientation* after the adoption of Twitter, this adoption would be effective mostly when the district has a clear prochoice or prolife opinion about abortion. In these cases, the politicians will become more inclined to hold the same *voting orientation* after adopting social media.

Table 13. Impact of Twitter Adoption on Abortion Bills

	DV = Representative's *prochoice score*							
	Including HRES505				Excluding HRES505			
	Model 21	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28
Twitter status	0.393*** (0.102)	0.259* (0.104)	0.514** (0.174)	0.335 (0.186)	0.387*** (0.111)	0.245* (0.112)	0.531*** (0.153)	0.343* (0.154)
Twitter status × District's *prochoice score*		0.615*** (0.093)		0.942*** (0.172)		0.683*** (0.099)		0.977** (0.145)
Robust	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Representative fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
R-squared (within)	0.319	0.331			0.031	0.052		
N	2,542	2,542	2,542	2,542	2,118	2,118	2,118	2,118
F-statistic	169.66	156.442			11.161	16.492		
Prob > *F*	<0.001	<0.001			<0.001	<0.001		
Specification	FE	FE	Fractional logit	Fractional logit	FE	FE	Fractional logit	Fractional logit

Notes. We used robust standard errors. We could not obtain goodness-of-fit statistics for fractional logit models.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

To better understand how the adoption of Twitter by representatives could influence their *voting orientation* in Congress, we studied the relationship between abortion-related tweets and representatives' *prochoice score*. From our handle_mentions tweets repository, we obtained all the abortion-related tweets posted from one week prior to the vote on each of the abortion bills to the day of voting on the bill.[20] Two aspects of these tweets were studied: (1) the volume of tweets and (2) the opinions in the tweets. We again used specification 3 to examine the impact of volume of tweets related to abortion on representatives' prochoice *voting orientation*. Table 14 reports the results. The results in Models 29, 31, 33, and 35 indicate that the volume of tweets by itself is not directly influential in changing a representative's prochoice *voting orientation*. However, similar to our previous findings, the volume of the tweets is influential if the district has a distinct prochoice or prolife opinion (Models 30, 32, 34, and 36).

To examine the potential effects that the opinions in the tweets had on representatives' prochoice *voting orientation*, we took two approaches (please refer to Online Appendix I for details):

1. Determine the prochoice sentiment of the tweets. We performed sentiment analysis on the tweets by using four different methods in the Syuzhet package

Table 14. Impact of *Frequency of Tweets* on Representatives' *Prochoice Score*

	DV = Representative's *prochoice score*							
	Including HRES505				Excluding HRES505			
	Model 29	Model 30	Model 31	Model 32	Model 33	Model 34	Model 35	Model 36
Abortion tweets count	0.052 (0.036)	0.038 (0.037)	0.061 (0.055)	0.157 (0.085)	0.052 (0.039)	0.038 (0.039)	0.063 (0.050)	0.161* (0.078)
Abortion tweets count × District's *prochoice score*		0.070** (0.022)		0.255* (0.112)		0.065** (0.023)		0.254* (0.103)
Robust	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Representative fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
R-squared (within)	0.319	0.322			0.024	0.029		
N	2,542	2,542	2,542	2,542	2,118	2,118	2,118	2,118
F-statistic	163.433	142.128			8.341	8.250		
Prob > *F*	<0.001	<0.001			<0.001	<0.001		
Specification	FE	FE	Fractional logit	Fractional logit	FE	FE	Fractional logit	Fractional logit

Note. We used robust standard errors.
$^{*}p < 0.05$; $^{**}p < 0.01$.

Table 15. Impact of Sentiment of Tweets on Representatives' *Prochoice Score*

	DV = Representative's *prochoice score*			
	Model 37	Model 38	Model 39	Model 40
Abortion tweets' prochoice sentiment	0.536 (0.308)	0.489 (0.371)		
Abortion tweets' prochoice sentiment × District's *prochoice score*		−0.091 (0.396)		
Abortion tweets' prochoice ratio			0.008 (0.021)	0.069 (0.063)
Abortion tweets' prochoice ratio × District's *prochoice score*				0.057 (0.056)
Robust	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Representative fixed effects	✓	✓	✓	✓
R-squared (within)	0.025	0.025	0.023	0.024
N	2,118	2,118	2,118	2,118
F-statistic	8.583	7.157	7.995	6.835
Prob > *F*	<0.001	<0.001	<0.001	<0.001
Specification	FEs	FEs	FEs	FEs

Notes. Representatives' votes on Dr. Tiller's shooting have been removed from the analysis. The estimations were replicated using a fractional logit model. The results are still not significant.

in R (Jockers 2016), then averaging the four sentiment scores. We aggregated these data for each time period (one week prior to voting) for each representative.

2. Determine the proportion of prochoice tweets to prolife tweets. In this approach, for each representative for each time period, we divided the number of tweets that mentioned #prochoice by the number of tweets that mentioned #prolife.

Each of the above methods results in a score that measures Twitter users' prochoice sentiments. We again used specification 3 to examine the effects of tweet content on representatives' *prochoice score*. Given the results reported in Table 15, the content of the tweets as measured by sentiment and the proportion of prochoice tweets to prolife tweets has no impact on representatives' *prochoice score*.

A comparison of the results in Tables 14 and 15 reveals an interesting pattern: given the constituents' *prochoice score*, the volume of the tweets related to abortion could influence the representative's prochoice *voting orientation*. However, such a relationship was not observed between Twitter users' prochoice sentiment (as measured by sentiment and proportion of prochoice to prolife tweets) and representatives' prochoice *voting orientation*. Therefore, the mechanism of influence seems to be related to the volume rather than to Twitter users' opinions about abortion.

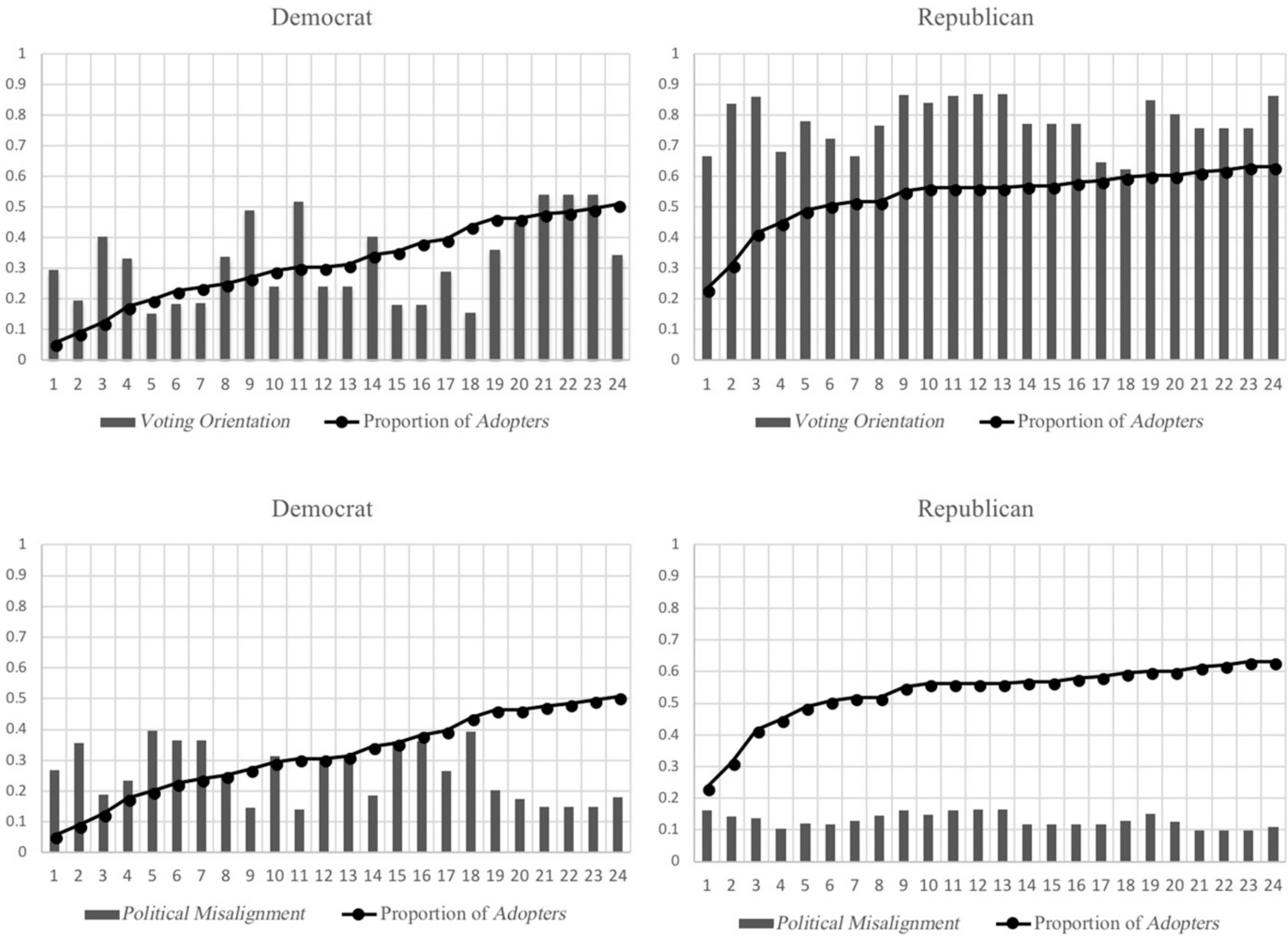
Our finding suggests that, when certain issues receive a significant amount of attention from Twitter users (high volume of tweets), the representatives infer that bills related to those issues are important to the public and thus vote more aligned with constituents' opinions on those bills. However, the representatives may be skeptical about Twitter sentiments they received as the Twitter users may not be their constituents and their Twitter sentiments may not reflect those of their constituents. Therefore, the representatives seek other resources to learn more about their constituents' true opinions about those bills. In this process, representatives vote in a manner more aligned with constituents' opinions about the bills when the constituents have strong opinions about the issues discussed in those bills but their votes are not significantly influenced by Twitter sentiments regarding those issues. The key here is that Twitter (along with traditional media) would help the representatives identify bills that are important to their constituents and thereby vote according to their preference.

6. Discussion

An online social network such as Twitter allows politicians to better interact with their constituents and potentially gauge constituents' opinions about bills/issues. Because OSNs enable voters to share their political views, their preferences, and the issues they face in their communities, these platforms could contain useful information for politicians. Although Twitter data is public and available to everyone, politicians who create accounts and actively engage in the Twittersphere would have a higher chance of observing voter discussions on Twitter.

According to Tables 5 and F (reported in Online Appendix F), the presence of Twitter would not only influence *voting orientation* and *political misalignment* but also the extent to which representatives (Table 5) and constituents (Table F in Online Appendix F) use

Figure 2. Trends in Proportion of *Adopters*, *Voting Orientation*, and *Political Misalignment* in the 111th House of Representatives



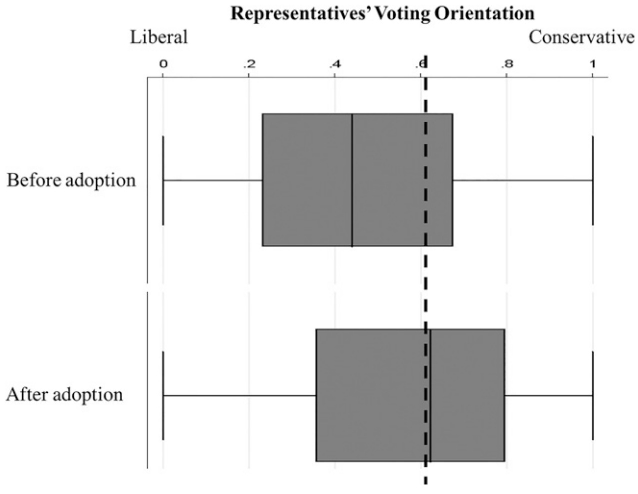
Twitter for political communication. From this perspective, OSNs can provide politicians with useful information about the issues that matter to voters. Because of these effects of OSN platforms on political involvement, as evidenced by our results, the adoption of OSNs by politicians may help them further align themselves with their constituents.

Figure 2 breaks down the effects of Twitter adoption on *voting orientation* and *political misalignment* for Democrats and Republicans. The lines in this figure refer to the proportion of *adopters* to the total number of representatives from the corresponding political party. In the upper plots, *voting orientation* can be compared to the proportion of *adopters*. For both Republicans and Democrats, there is an upward trend in the proportion of *adopters* as well as *voting orientation.* The lower plots show the reverse relationship between the proportion of *adopters* and *political misalignment.*

Another way to visualize the overall effect of adoption on *political orientation* and *political misalignment* is to compare the range of *voting orientation* before and after adoption with the constituents' *political ideology.* Figure 3 shows that although the politicians became more conservative after adoption. Their mean *voting orientation* is closer to the mean of constituents' *political ideology*. To better understand why representatives became more conservative after adoption, we compared representatives from the two parties with respect to proportion of *adopters*, number of months active on Twitter, number of tweets by the representatives, and the number of representatives' handle mentions in the Twittersphere. Figure 4 illustrates a significantly higher engagement by Republicans.[21]

A higher proportion of Republican representatives adopted Twitter and was active on Twitter during the 111th Congress. Also, they were mentioned more, and they tweeted more than did their peers across the aisle. Along with our results that show a slightly higher alignment between representatives and their constituents after the adoption of Twitter, we discovered that the adoption of Twitter by representatives could help them better reflect their constituents' views on important issues such as abortion. Representatives move in the direction of a constituent's position after the adoption of Twitter only if the constituent has a strong position on that issue (i.e., distinctly in favor of

Figure 3. Impact of Twitter Adoption on *Voting Orientation* of Representatives Who Joined Twitter During the 111th Congress

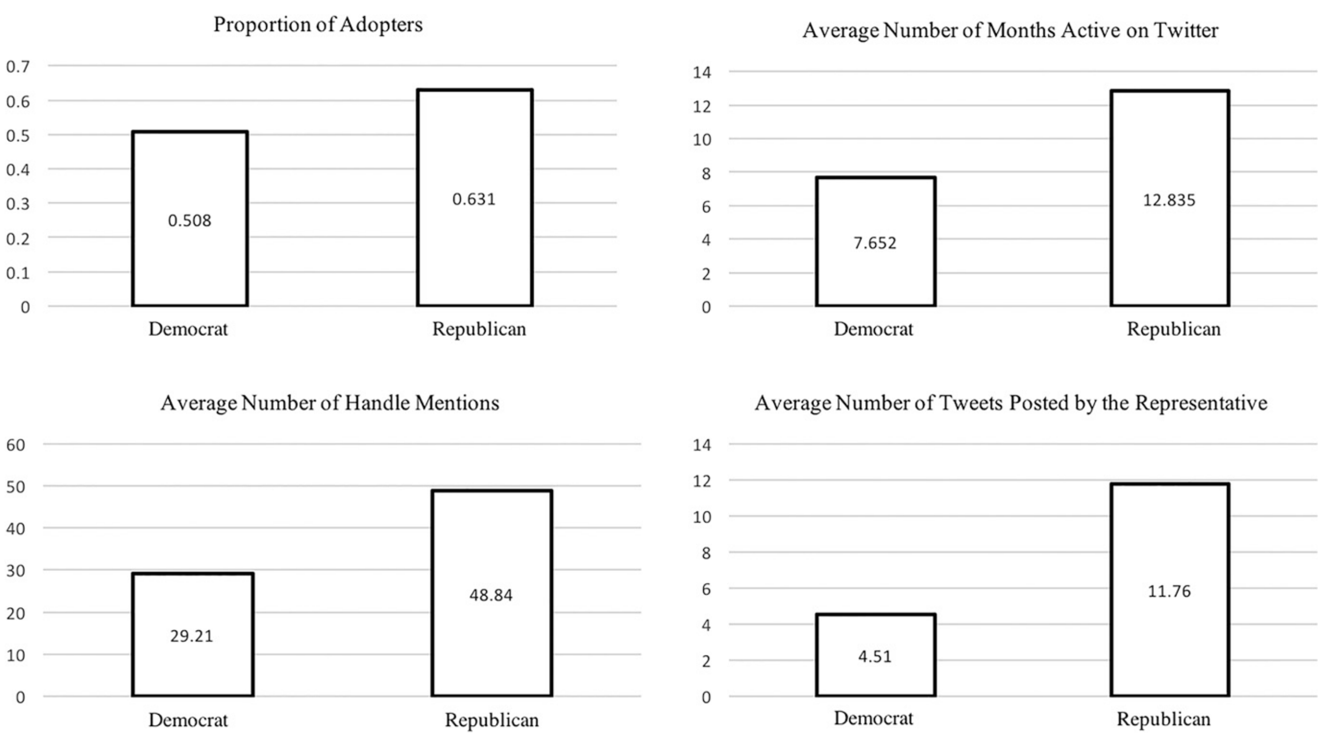


Note. The dashed line represents the *political ideology* of *adopters'* constituents.

or distinctly against). To further study the mechanism of influence of Twitter adoption on representatives' *voting orientation*, we analyzed the volume and content of abortion-related tweets addressed to representatives. Our analysis revealed that the volume of tweets could help the representative vote in a manner more aligned with the constituent regarding the issue of abortion. On the other hand, we did not find a significant relationship between the content and Representative's *prochoice score.*

According to a report published by the Congressional Management Foundation (Fitch and Goldschmidt 2015, p. 10), although 76% of representatives and their staff members believe that social media enabled them "to have more meaningful interactions with constituents," they generally do not feel that social media posts provide enough information to identify constituents. Another important finding of this report relates to the number of comments that may catch their attention; 35% of respondents (Congressional staffers) mentioned that even fewer than 10 social media comments may catch their attention. To understand the importance of the volume of social media comments (such as tweets), it would be helpful to consider representatives' legislative workload throughout a two-year service in Congress. During their service in the U.S. Congress, the 111th House Representatives worked on 13,675 legislative pieces (GovTrack 2016), of which 1,655 required a roll-call vote (Congress.gov 2016). According to an article published in the Economist (2013), each bill has an average length of 20 pages. Given this amount of legislative material to consider while serving in Congress, representatives could potentially use social media to identify bills that contain issues of importance to their constituents. Even if representatives ignore the content or the position taken in the Twittersphere (because of the user's unknown identity), they may still think that the issues or bills are important to voters and, therefore, to their own constituents. Hence,

Figure 4. Twitter Engagement of Democrats and Republicans



they can allocate more time and resources to those bills as a means of reflecting their constituents' opinions.

7. Conclusion and Limitations

Previous studies suggest that online social networking has caused numerous societal, economic, and cultural changes. However, the impact of online social media on politics and policy making has not been adequately explored. To study the impact of online social media on the *voting orientation* of politicians, we constructed a panel data for 445 members of the 111th U.S. House of representatives across a period of 24 months using three disparate data sets. We collected representatives' data, including their voting records, their Twitter data, and constituents' data. Our analysis revealed that the adoption of Twitter directs representatives toward the conservative side of the political spectrum. Given that the representatives were more liberal than their constituents before adoption (Figure 3), the move toward the conservative side could indicate more alignment between representatives and their constituents. Furthermore, we found that representatives' adoption of Twitter drives them to vote closer to their constituents' *political ideology*. Our analysis also reveals that although the opinions in user-generated tweets may not influence representatives' *voting orientation* with respect to a given issue, the volume of tweets could help representatives identify important bills or issues and become more aligned with their constituents.

One of the limitations of this study relates to the sample. U.S. Representatives are elite politicians whose decision making in politics would differ from that of regular people. Thus, the generalizability of these findings could be limited. We also note that the similarity of the names of some representatives and other users could distort the accuracy of name_mention tweets collected from Twitter. Although natural language processing methodologies (Zhang and Ram 2015) would allow for the identification of tweets relating to a given topic, we could not find a practical approach for determining the percentage of tweets that were, indeed, about the representatives. As a cross check, we created a list of representatives with common names (for instance, Jim Cooper and Mike Ross) and checked the correlation between name-mention tweets and handle_mention tweets for these representatives. We observed a very high correlation between the two, signaling potential high accuracy for name_mention tweets.

Another limitation with regard to name_mention tweets and handle_mention tweets is that we do not know whether constituents sent these tweets. However, we argue that this information, for the most part, was not available to the representatives. We also recognize that, if available, the representatives may give greater weight to tweets posted by their own constituents as opposed to other tweets. Finally, a dynamic monthly measure of constituents' *political ideology* could have helped us construct a more accurate measure for *political misalignment*. However, to the best of our knowledge, all the measures developed for constituents' *voting orientation* are for time periods of four years or longer, as these measures are developed, at least partly, based on presidential election data or national survey data administered throughout the years (Kernell 2009, Tausanovitch and Warshaw 2013).

Aside from these limitations, this study reveals that the use of social media could help representatives understand which issues and policies matter to their constituents. Hence, when voting on bills in Congress, they can become more aligned with their constituents' preferences. Voters, therefore, could take advantage of representatives' presence on social media to voice their opinions.

Acknowledgments

The authors thank Dr. Gedas Adomavicius (senior editor), Dr. Michael Zhang (associate editor), and the anonymous reviewers who supported us and provided us with helpful guidelines to improve this study. The authors also thank our discussant (Dr. Jason Chan) at the Workshop on Information Systems Economics (WISE 2015) and anonymous reviewers at 2014 INFORMS Conference on Information Systems (CIST 2014) and Hawaii International Conference on System Sciences (HICSS 2016). The authors are grateful to seminar participants at Georgia Institute of Technology, Michigan State University, Texas A&M University, Nanyang Technological University, and Texas Tech 2015 Big Data Symposium for their constructive feedback and comments. The authors are grateful to political scientists Dr. Georgia Kernell, Dr. Chris Tausanovitch, Dr. Patrick Kenney, Dr. Kim Fridkin, and Dr. Keith Poole who helped us better understand the relevant concepts in their field. The authors are grateful to the data science initiative at the University of North Carolina–Charlotte for their help in collecting data.

Endnotes

[1] The U.S. Congress comprises two chambers: (1) the U.S. Senate and (2) the U.S. House of Representatives. Senators represent their states, whereas representatives represent their congressional districts. Each state comprises one or more congressional districts. Given the larger size of the U.S. House of Representatives, we focus only on this chamber. Voters in each congressional district elect their district's representative for a two-year term.

[2] Please refer to Online Appendix A for additional information about the number of representatives in the House of Representatives.

[3] Please refer to Online Appendix B for additional information about WNOMINATE and our estimation procedure.

[4] In the trustee model of representation, the elected representative ideally considers the views of constituents as well as the facts. However, the elected representative is entrusted with the final judgment.

[5] Please refer to Online Appendix C for the details of our data collection process.

[6] These data were collected from another website that indexed Twitter data. For more information, please refer to Online Appendix C, the section about Topsy.

[7] We used the exact first name and last name used in the Library of Congress database. Representatives Mike Rogers (R MI 8) and Mike Rogers (R AL 3) were dropped because of the similarity of their names. We did not have a practical approach for determining whether the tweet was indeed about the representative or someone else with the same first and last names. This is one of the limitations of this study.

[8] For representatives from Alaska, Delaware, Montana, North Dakota, South Dakota, Vermont, and Wyoming, we used a default value of zero for *neighbor effect*, as these states each have only one representative. We also removed these states and replicated the estimations. The results were similar to those reported in the manuscript.

[9] We added 1 to the number of tweets before taking the log to prevent the issue with log of 0.

[10] It should be noted that we were unable to determine which tweets were from which congressional district. Therefore, it is not clear whether the tweet was, indeed, from a constituent. Although this would be regarded as a limitation of this study, we argue that this information is mostly not available to the representatives either.

[11] We also ran PSM to compare *adopters* and the pool of *not-yet adopters* and *never adopters*. The results were similar to the results reported in Table 7.

[12] The analysis is based on each month during which at least 10 representatives adopted Twitter, excluding the first month (January 2009). We did not include January 2009 because the representatives' voting orientation is not observed before this period. We used the guidelines provided by Peduzzi et al. (1996) to determine the minimum sample size for the logit model in our PSM approach. This guideline suggested at least 20 samples (10 *adopters* and 10 *non-adopters*) are needed.

[13] We also counted the number of representatives' tweets posted from an iPhone using a random sample drawn from another data set. We found that over 11% of the tweets posted by representatives in 113th Congress were sent from an iPhone.

[14] Because the district-level data could not be obtained, we used data from http://blog.hubspot.com/blog/tabid/6307/bid/7905/Twitter-Usage-Per-Capita-How-States-Compare-Infographic.aspx. This source of data represents a transformed measure for overall Twitter usage per capita for each state. The data in this source are based on overall Twitter usage in 2010 (Online Appendix G).

[15] Constituents' scores, household income, unemployment rate, and the percentage of high school graduates were used as control variables.

[16] Because 204 actual representatives adopted Twitter during the 111th Congress, we used 204 adopters in our simulation to create the placebo data.

[17] This decision was primarily made because of the availability of data regarding the issue of abortion. Because we needed a reliable policy preference score for the congressional districts, we used Warshaw and Rodden's district level scores (Warshaw and Rodden 2012). They estimated the preferences of constituents on six issues: abortion, the environment, gay marriage, minimum wage, social security, and stem cells. Among all these issues, we focused on abortion and environmental protection because there were several bills related to these issues in the 111th House of Representatives and also because there are clear yes or no answers to those bills. With respect to the content that Twitter uses shared, we found only a few relevant tweets about environmental protection that qualified for inclusion in our study. Therefore, we studied the mechanism of influence by focusing only on the issue of abortion. Refer to Online Appendix I for more information about data collection and processing. The scripts for estimations and input data for all issues are available at http://cwarshaw.scripts.mit.edu/WarshawRodden_ReplicationData.php.

[18] Please refer to Online Appendix C for more information about our data collection process.

[19] For instance, the term "abortion" is mentioned in HR20 of the 111th Congress, but it is not a position-taking bill, as it simply assigns the Director of the National Institute of Mental Health to conduct a nationally representative longitudinal study of the relative mental health consequences for women of resolving a pregnancy in various ways, including carrying the pregnancy to term and parenting the child, carrying the pregnancy to term and placing the child for adoption, miscarriage, and having an abortion. Online Appendix H includes our explanation of the scores assigned to these bills.

[20] Online Appendix I describes our approach for preparing the data for this section.

[21] All the comparisons are statistically significant. These results align with previous reports: http://piperreport.com/blog/2013/04/15/congress-social-media-twitter-facebook-senators-congressmen/.

References

Aldrich JH, Battista JSC (2002) Conditional party government in the states. *Amer. J. Political Sci.* 46(1):164–172.

Aldrich JH, Montgomery JM, Sparks DB (2014) Polarization and ideology: Partisan sources of low dimensionality in scaled roll call analyses. *Political Anal.* 22(4):435–456.

Andrade AD, Doolin B (2016) Information and communication technology and the social inclusion of refugees. *MIS Quart.* 40(2):405–416.

Bertot JC, Jaeger PT, Grimes JM (2010) Using ICTs to create a culture of transparency: E-Government and social media as openness and anti-corruption tools for societies. *Gov. Inform. Quart.* 27(3): 264–271.

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *Quart. J. Econom.* 119(1):249–275.

Bond RM, Fariss CJ, Jones JJ, Kramer ADI, Marlow C, Settle JE, Fowler JH (2012) A 61-million-person experiment in social influence and political mobilization. *Nature* 489(7415): 295–298.

Bonica A (2014) Mapping the ideological marketplace. *Amer. J. Political Sci.* 58(2):367–386.

Burmester N, Jankowski M (2014) The EU in the United Nations General Assembly: A comparative perspective. *4th European Union in Internat. Affairs Conf., May 22–24, Brussels*, 1–26.

Burt R (1992) *Structural Holes: The Social Structure of Competition* (Harvard University Press, Cambridge, MA).

Carter L, Bélanger F (2005) The utilization of E-government services: Citizen trust, innovation and acceptance factors. *Inform. Systems J.* 15(1):5–25.

Chan J, Ghose A (2014) Internet's dirty secret: Assessing the impact of online intermediaries on HIV transmission. *MIS Quart.* 38(4): 955–976.

Chen H, Chiang RHL, Storey VC (2012) Business intelligence and analytics: From big data to big impact. *MIS Quart.* 36(4):1165 –1188.

Clinton J (2006) Representation in Congress: Constituents and roll calls in the 106th House. *J. Politics* 68(2):397–409.

Congress.gov (2016) Roll call votes by the U.S. Congress. Accessed October 23, 2016, https://www.congress.gov/roll-call-votes.

Congressional Management Foundation (2011) #SocialCongress: Perceptions and use of social media on Capitol Hill. Accessed June 18, 2015, http://www.congressfoundation.org/storage/documents/CMF_Pubs/congress.pdf.

Debating Europe (2013) How is social media changing politics? Accessed June 19, 2015, http://www.debatingeurope.eu/2013/01/22/how-is-social-media-changing-politics/#.VNjKffnF92A.

DiPrete TA, Gangl M (2004) Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociol. Methodol.* 34(1):271–310.

Dranove D, Kessler D, Mcclellan M, Satterthwaite M (2003) Is more information better? The effects of 'report cards' on health care providers. *J. Political Econom.* 111(3):555–588.

Economist (2013) Outrageous bills: Why Congress writes such long laws. Accessed October 23, 2016, http://www.economist.com/news/united-states/21590368-why-congress-writes-such-long-laws-outrageous-bills.

Edvardsson B, Tronvoll B, Gruber T (2011) Expanding understanding of service exchange and value co-creation: A social construction approach. *J. Acad. Marketing Sci.* 39(2):327–339.

Fitch B, Goldschmidt K (2015) #Social Congress 2015. Congressional Management Foundation, Washington, DC. http://www.congressfoundation.org/storage/documents/CMF_Pubs/congress.pdf.

Ganju KK, Pavlou PA, Banker RD (2016) Does information and communication technology lead to the well-being of nations? A country-level empirical investigation. *MIS Quart*. 40(2):417–430.

Ghobadi S, Clegg S (2015) 'These days will never be forgotten...': A critical mass approach to online activism. *Inform. Organ.* 25(1):52–71.

Glassman M (2017) Congressional member organizations: Their purpose and activities, history, and formation. Congressional Research Services Report, Washington, DC.

Goh K-Y, Heng C-S, Lin Z (2013) Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content. *Inform. Systems Res.* 24(1):88–107.

Golbeck J, Grimes JM, Rogers A (2010) Twitter use by the U.S. Congress. *J. Assoc. Inform. Sci. Tech.* 61(8):1612–1621.

Goldschmidt K, Ochreiter L (2008) *Communicating with Congress: How the Internet Has Changed Citizen Engagement* (Congressional Management Foundation, Washington, DC).

GovTrack (2016) Statistics and historical comparison. Accessed October 23, 2016, https://www.govtrack.us/congress/bills/statistics.

Greenberg SR (2012) Congress + social media. Working paper, Lyndon B. Johnson School of Public Affairs, The University of Texas at Austin.

Hattem J (2014) Which phone do lawmakers like the most? Accessed September 16, 2015, http://thehill.com/policy/technology/220096-lawmakers-pick-iphones-over-droids.

Jin GZ, Leslie P (2003) The effect of information on product quality: Evidence from restaurant hygiene grade cards. *Quart. J. Econom.* 118(2):409–451.

Jockers M (2016) Package Syuzhet: Extracts sentiment and sentiment derived plot arcs from text. Accessed September 2, 2016, https://cran.r-project.org/web/packages/syuzhet/syuzhet.pdf.

Kernell G (2009) Giving order to districts: Estimating voter distributions with national election returns. *Political Anal.* 17(3):215–235.

Kieschnick R, McCullough BD (2003) Regression analysis of variates observed on (0, 1): Percentages, proportions and fractions. *Statist. Modelling* 3(3):193–213.

Leuven E, Sianesi B (2014) PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Statistical Software Components, Boston College Department of Economics. Accessed November 4, 2014, http://ideas.repec.org/c/boc/bocode/s432001.html.

Linders D (2012) From E-government to we-government: Defining a typology for citizen coproduction in the age of social media. *Gov. Inform. Quart.* 29(4):446–454.

Luo X, Zhang J, Duan W (2013) Social media and firm equity value. *Inform. Systems Res.* 24(1):146–163.

Lupu Y (2013) The informative power of treaty commitment: Using the spatial model to address selection effects. *Amer. J. Political Sci.* 57(4):912–925.

McCarty N, Poole KT, Rosenthal H (2008) *Polarized America: The Dance of Ideology and Unequal Riches* (MIT Press, Cambridge, MA).

Mitchell A, Hitlin P (2013) Twitter reaction to events often at odds with overall public opinion. Accessed December 4, 2017, http://www.pewresearch.org/2013/03/04/twitter-reaction-to-events-often-at-odds-with-overall-public-opinion/.

Peduzzi P, Concato J, Kemper E, Holford TR, Feinstein AR (1996) A simulation study of the number of events per variable in logistic regression analysis. *J. Clin. Epidemiol.* 49(12):1372–1379.

Peterson RD (2012) To Tweet or not to Tweet: Exploring the determinants of early adoption of Twitter by House members in the 111th Congress. *Soc. Sci. J.* 49(4):430–438.

Piper K (2013) Congress and social media: Use of Twitter and Facebook by senators and congressmen. Accessed October 23, 2016, http://www.piperreport.com/blog/2013/04/15/congress-social-media-twitter-facebook-senators-congressmen.

Poole K, Lewis J, Lo J, Carroll R (2011) Scaling roll call votes with WNOMINATE in R. *J. Statist. Software* 42(14):1–21.

Poole KT, Rosenthal H (1985) A spatial model for legislative roll call analysis. *Amer. J. Political Sci.* 29(2):357–384.

Poole KT, Rosenthal H (2007) *Ideology & Congress* (Transaction Publishers, Piscataway, NJ).

Riggins FJ, Dewan S (2005) The digital divide: Current and future research directions. *J. Assoc. Inform. Systems* 6(12):298–337.

Rishika R, Kumar A, Janakiraman R, Bezawada R (2013) The effect of customers' social media participation on customer visit frequency and profitability: An empirical investigation. *Inform. Systems Res.* 24(1):108–127.

Ruths D, Pfeffer J (2014) Social media for large studies of behavior. *Science* 346(6213):1063–1064.

Selander L, Jarvenpaa S (2016) Digital action repertoires and transforming a social movement organization. *MIS Quart.* 40(2):331–352.

Stone B (2010) Twitter for iPhone. Accessed April 12, 2014, https://blog.twitter.com/official/en_us/a/2010/twitter-for-iphone.html.

Sun M, Zhu F (2013) Ad revenue and content commercialization: Evidence from blogs. *Management Sci.* 59(10):2314–2331.

Tausanovitch C, Warshaw C (2013) Measuring constituent policy preferences in Congress, state legislatures, and cities. *J. Politics* 75(2):330–342.

Valenzuela S (2013) Unpacking the use of social media for protest behavior: The roles of information, opinion expression, and activism. *Amer. Behav. Sci.* 57(7):920–942.

Victor JN (2013) U.S. Congress caucus data. Accessed July 11, 2016, http://mason.gmu.edu/~jvictor3/Data/.

Warshaw C, Rodden J (2012) How should we measure district-level public opinion on individual issues?" *J. Politics* 74(1):203–219.

Wattal S, Schuff D, Mandviwalla M, Williams CB (2010) Web 2.0 and politics: The 2008 U.S. Presidential election and an E-politics research agenda. *MIS Quart.* 34(4):669–688.

Williams R (2016) Analyzing proportions: Fractional response and zero one inflated beta models. Working paper, University of Notre Dame, Notre Dame, IN.

Wu L (2013) Social network effects on productivity and job security: Evidence from the adoption of a social networking tool. *Inform. Systems Res.* 24(1):30–51.

Zhang W, Ram S (2015) A comprehensive methodology for extracting signal from social media text using natural language processing and machine learning. *Proc. Workshop Inform. Tech. Systems, Dallas*, 1–16.