The Impact of Twitter Adoption on Lawmakers' Voting Orientations

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Abstract

Organizations have been using social media extensively to learn about their current and potential customers, but little is known if such endeavors truly influence organizations' decisions to make them closer to their customers. This paper studies this question in a unique context – the impact of U.S. Representatives' Twitter adoption on their voting orientations in The Congress. In particular, we consider whether the adoption of Twitter by Representatives makes them to 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 exploit 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-difference approaches along with Propensity Score Matching to address potential endogeneity in Representatives' Twitter adoption decisions, we found that the adoption of Twitter by Representatives makes them to vote more in line with their constituents. We also found that the effect of Twitter adoption is more salient, when a Representative's party differs from the party affiliation of his/her district and when Twitter use per capita is higher in a Representative's state

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Keywords: Online Social Media, Twitter, Societal Impact of IS, Decision-Making in Politics, U.S. House of Representatives, Panel Data, Difference-in-Difference Model

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 the societies can be observed in numerous cases. For example, microblogging platforms, such as Twitter, have been widely credited as a key enabler of Arab Spring, Spain and Portugal movements in 2011, and Turkey and Brazil movements in 2013. OSN platforms are known to facilitate the participations of consumers and the public in business (Edvardsson et al. 2011; Goh et al. 2013; Luo et al. 2013; Rishika et al. 2013), government decision making processes (Bertot et al. 2010; Linders 2012), and political campaigns (Bond et al. 2012; Wattal et al. 2010). However, little is known about the degree to which such participations truly affect firms or organizations' decision outcomes.

The U.S. political system provides a rare opportunity where the most important decision outcomes made by U.S. politicians – voting decisions– are observable to the public. Additionally, 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% percent of the U.S. Representatives 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 percent had both Twitter and Facebook accounts (Riper 2013). Moreover, the analysis of the post contents by Representatives in Greenberg's study revealed that the majority of them are politically relevant posts. Online social media not only help lawmakers to communicate their messages to the constituents, but also provide the constituents with a channel to interact with their representatives in a convenient way. According to a Congressional Management Foundation report based on a survey on 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) According to another report by 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). Golbeck et al. (2010) analyzed all of the tweets posted by Members of Congress during a two-month period and discovered that 7.4% of the tweets posted by Members are 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)

Figure 1. Representative Mike Honda's (D- CA 17) Website Reveals the Importance of Social Media for Politicians

Overall, the adoption and use of online social networks by politicians has the potential to facilitate communications between constitutes and Representatives. However, it is not clear to what extent the adoption and use of Twitter by Representatives truly influences the political decisions of the Representatives

This study contributes to the stream of IS research on the societal and political impact of online social networks. OSN platforms have been known for empowering citizens, and improving transparency, participation, and equality (Chen et al. 2012). However, the focus of the extant literature has been on participation and engagement with the new media and less on the societal outcomes. In this research, we use the U.S. Representatives' voting orientations to assess to what degree the public influences organizational decisions through OSN platforms. In particular, we examine whether the adoption of OSNs 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 of the analyses. We discuss our findings and conclude with limitations and potential extension of this study in Sections 6 and 7.

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), prevalence of HIV (Chan and Ghose 2014), social inclusion of refugees in the host society (Andrade and Doolin forthcoming), and well-being of nations (Ganju et al. forthcoming). In addition, particularly after President Obama's successful social media campaign in 2008, researchers in a variety of other disciplines including political science have examined the role of online technologies such OSN platforms on political environment.

All of the studies mentioned above unveiled 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 could work as networks hosting useful information and therefore could allow users to access more information in a timely manner. Furthermore, the users can obtain recommendations from trusted acquaintances. These mechanisms may change users' decisions and, therefore, their performance (Wu 2013). Overall, this perspective focuses on information cascaded within the network. A new user who joins a network has the opportunity to seek new information within the network. Regardless whether the user is a patient who seeks relevant information to deal with the illness, or a buyer who seeks information about a certain type of product, information-rich networks could help the user in achieving their goals. For politicians, an information-rich network is a network that allows them to seek information from constituents. After all, politicians are representing the constituents and need to understand their preferences when making decisions in Capitol Hill. OSNs provide information-rich networks for politicians as these networks contain rich real-time information about the constituents, their behaviors, and their preferences. According to Adam Conner, President Obama's campaign social media strategist, "When it comes to receiving advice, our leaders may find it better to listen to a housewife, [rather than] a detached-from-reality financier [who only wants to] make profit and practice what he was taught in Harvard… So, if I was our leaders, I would pay more attention to what the people have to say in social media and blogs…" (Debating Europe 2013) In another statement he claims: "[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) Therefore, not only OSN platforms provide politically active constituents with an open channel to communicate with the politicians, but also they provide a new way for less politically-active citizens to be heard by their representatives. For instance, a study of 61 million of Facebook users on 2010 Election Day found that political messages in OSNs have a measurable effect on political self-expression, information seeking and real-world voting behavior of millions of people (Bond et al. 2012). Another study conducted by The European Parliament found that the new media (OSNs) may help women to achieve a higher level of political involvement (OpCit Research 2013). In this perspective, OSNs can allow the politicians to interact with less politically-involved citizens and therefore a more representative sample of the constituents and their preferences. Due to these effects of OSN platforms, we propose that the adoption of OSNs by politicians can help them to vote more in line with the wish of their constituents.

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.

3.1. Dependent Variables

Spanning the 111th Congress, we estimate the monthly measure of Representatives' voting orientations based on votes cast by each Representative 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).[1] 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., Yea or Nay) over a series of congressional votes, WNOMINATE produces a configuration of legislators and outcome points for the Yea and Nay alternatives for each roll call using a probabilistic model of choice. WNOMINATE creates a spectrum of scores ranging from -1 to +1, with -1 representing the most liberal Representative and +1 representing the most conservative Representative (Figure 2). It is worth mentioning that the WNOMINATE scores have been widely employed by political scientists to study the behaviors of the politicians based on their voting records (Aldrich and Battista 2002; Aldrich et al. 2014; Lupu 2013).

To study the extent of *political misalignment* between Representatives and their constituents, we needed to obtain a measure for political ideology of the constituents in addition to Representatives' *voting orientation*. We obtained such measure from Tausanovitch and Warshaw (2013). Similar to WNOMINATE

[1] Please refer to Appendix A for further information about WNOMINATE and our estimation procedure.

scores for Representatives, constituents' scores measure the average policy preferences by estimating the extent to which a Congressional district leans toward Democrat or Republican parties. To estimate the constituents' scores, Tausanovitch and Warshaw employ item response theory to jointly 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. It is worth noting that this measure has been employed in other empirical studies to capture the political ideology of the constituents (Bonica 2014). Since the scale of constituents' estimates are different from that of WNOMINATE estimates, we normalized both estimates using Min-Max-Scaling such that both estimates range from zero to one, with zero being the most liberal Representative/ Congressional district and one being the most conservative Representative/ Congressional district.

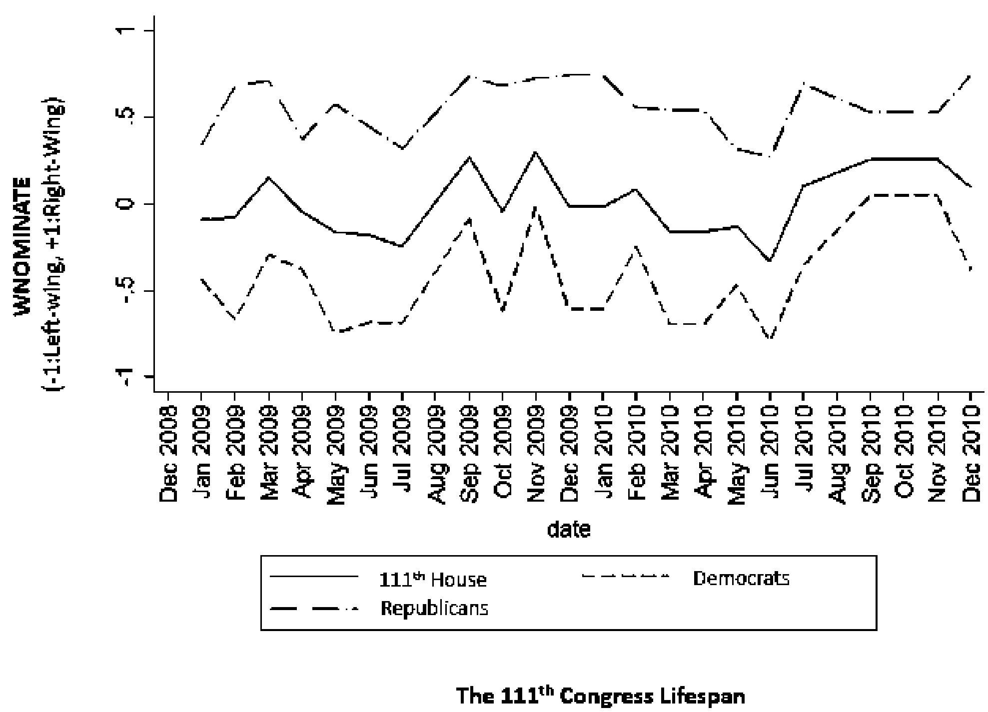

Figure 2. Average WNOMINATE scores for Members of 111th House of Representatives

3.2. Predictor and Control Variables

To capture the dates Representatives adopted Twitter, we made API calls to Twitter API and Sunlight Foundation's Congress API, which helped us to link Representatives' Twitter accounts to their legislative data. Out of 445 Representatives, 246 had Twitter accounts by the end of the 111th Congress. Among the 246 Representatives, 42 had an account before the start of the 111th Congress and 204 joined Twitter during the 111th Congress (January 2009 – December 2010). With this 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 zero otherwise. From Twitter, we also collected three more data sets: 1- All of the tweets posted by the Representatives during each month of the 111th Congress. A total of 67,366 tweets were collected from the Representatives' accounts. 2- All of the tweets in which the Representatives' Twitter handles (official usernames) were mentioned.[2] This data contains 394,389 tweets. 3- All of the tweets in which the Representatives' names (first name and last name) were mentioned.[3] A total of 1,553,442 tweets were recorded in this data.

We further collected data from The Library of Congress (THOMAS), U.S. Census, NY Times API, voteview.com, The Social Science Research Council (SSRC), and hubspot.com about the Representatives and their constituents. Table 2 provides the descriptions and the 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 orientations* is consistent with prior studies (Poole et al. 2011). The mean of

2 The Representatives' retweets were removed from this data set and only the mentions were kept.
3 We used the exact first name & last name that were used in the Library of Congress database. Representatives Mike Rogers (R- MI 8) and Mike Rogers (R- AL 3) were dropped due to the similarity of their names. It is worth noting that we did not have any practical approach to determine if the tweet is indeed about the Representative or someone else with the same exact first and last names. This is one of the limitations of this study.

Representative's voting orientations denotes that the 111th Congress was slightly leaned toward the conservative side of the political spectrum as it is larger than 0.5. The mean of Constituents' political ideology denotes that the constituents were also leaned toward the conservative side of the political spectrum.

Table 1. Summary Statistics of Variables[4]					
Variables	Observations	Mean	Std. Dev.	Min	Max
Representative's voting orientation	10537	0.505	0.274	0	1
constituent's political ideology	10680	0.614	0.184	0	1
political misalignment	10537	0.211	0.159	0	0.874
adopter	10680	0.553	0.497	0	1
twitter status	10680	0.404	0.491	0	1
tweets frequency	10680	6.308	17.589	0	385
handle-mentions frequency	10680	36.928	124.776	0	1637
Instrumental Variables:					
name-mentions frequency	10632	146.110	226.021	0	1923
committee effect	10680	16.954	24.990	0	122
neighbor effect	10680	0.363	0.186	0	0.875

Political misalignment captures the distance between the *Representative's voting orientations* and the *constituent's political ideologies*. 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

[4] Notes on Table 1: For months August 2009 and August 2010, the WNOMINATE scores were not estimated as the House of Representatives was in recess. We also excluded Representatives who voted on less than twenty bills during any given month (please refer to Appendix A). *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. *Name-mentions frequency* is the number of tweets in which the Representatives' first name & last name were mentioned on Twitter in any given month.

0.211. On average, the Representatives posted about 6 tweets during each month and their Twitter handles were mentioned about 37 times per month.

We construct three time-variant instrumental variable to account for the effects of time-variant unobservables. Valid instruments need to 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 name & last name were mentioned on Twitter sphere in any given month. We obtained 1,553,442 tweets by making API calls to Twitter API. Mentioning the Representative by first name and last name is not controlled by the Representatives. That is, every Twitter user can mention the Representatives even though they have not created a Twitter account. We believe that those Representatives who are mentioned frequently have a higher tendency to create an account and use this channel to communicate with the citizens. Therefore, we argue that the number of Representatives' name-mentions in Twitter sphere would be a good choice of instrument. According to Table 1, Representatives were mentioned 146 times per month on average.

Figure 3. Example of *name-mentions* for Representative John Dingell (D –MI 15) before He Joined Twitter

The second instrument (*committee effect*) is created by counting the number of peers (other Representatives) who joined Twitter at each time period t and who served at the same committees that Representative i is a member of. The rationale is that the choice to use Twitter among Representatives from the same committees may be correlated. That is, if more Representatives whom Representative i knows (and regularly interacts with in the committee meetings) adopt Twitter, Representative i may be more inclined to adopt as well. The value of this instrumental variable ranges from 0 to 122 with a mean of 17. We constructed the third instrument (*neighbor effect*) by counting the proportion of peers from Representative i's state who joined Twitter at 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). According to Table 1, one third of a given Representative's peers from the same state are on Twitter. It is worth noting that all three instruments were employed in models 1, 2, 4, and 5.

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

Table 2. Summary Statistics And Descriptions for Control Variables

Variable	Description	Source	Observations	Mean	Std. Dev.	Min	Max
age	Representative's age	THOMAS	10680	57.164	10.293	28	86
gender	Representative's gender (1 if male)	THOMAS	10680	0.829	0.376	0	1
seniority	The number of years Representative has been in the body (House or Senate) of which he or she is currently a member.	Sunlight API	10680	11.935	9.130	1	56
party vote	The percentage of votes in which the Representative's position agreed with the majority position in his or her party.	Sunlight API	10680	94.12	4.369	70.83	99.09
sponsorship	The number of bills sponsored by the Representative while in that particular role.	NY Times	10680	18.997	13.348	0	84
co-sponsorship	The number of bills co-sponsored by the Representative while in that particular role.	NY Times	10680	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	10680	4.693	6.990	0	93.4
household income	Mean logarithm household income in Representative's district.	U.S. Census	10680	10.827	0.252	10.084	11.532
highschool graduate	% of high school graduates in Representative's district	SSRC	10680	85.028	6.761	55.1	96.2
white	% of white population in Representative's district	SSRC	10680	76.529	17.667	16.04	98.12

4. Empirical Methodology

The adoption of Twitter by Representatives over time creates a quasi-natural experiment setting that allows the comparison of difference in voting orientations before and after adopting Twitter. We exploit the variation in joining Twitter across Representatives as the basis for identifying the impact of adopting Twitter on voting behavior. This strategy has been implemented in numerous research studies including (Chan and Ghose 2014; Dranove et al. 2003; Jin and Leslie 2003; Sun and Zhu 2013). We further address the endogeneity of adoption decision through using instrumental variables, propensity score matching, and external events and the serial correlation problem through using ignoring the time series data and randomization inference as proposed by Bertrand et al. (2004). To assess the effect of Twitter adoption on Representatives' voting behavior, we employ the following model:

$$y_{it} = \beta_0 + \beta_1 Q_i + \beta_2\, Q_i \times x_{it} + \sum_{j=1}^{24} \gamma_j MonthDummy_j + \epsilon_{it} \qquad (1)$$

where i is the index for Representatives and t is the index for time, t = 01-2009, 02-2009, … , 12-2010; Q_i is a dummy that takes the value of 1 if Representative i is an eventual adopter, and 0 otherwise. We call this variable "*adopter*". x_{it} (*twitter status*) is the binary variable for adopting Twitter, meaning that x_{it}=1 if Representative i has a Twitter account at time t and zero otherwise. We also include dummies for each month from January 2009 to December 2010 to control for changes in Representatives' average propensity to vote in favor of liberal or conservative initiatives. We use Specification (1) to study the impact of Representatives' adoption of Twitter on two response variables (y_{it}). For the first response variable, we use *Representatives' voting orientations* (normalized WNOMINATE). β_2 is our difference-in-differences estimator that captures the adoption's effect on voting orientations of the Representatives. A positive and significant value for β_2 means that the Representatives became more conservative after the adoption and a negative and significant value for β_2 means that the Representatives became more liberal. For the second response variable we use *political misalignment*. To construct *political misalignment*, we subtract normalized constituents' political ideology from each Congressman's voting orientations and take the absolute values. A decrease in *political misalignment* means that Representative is more aligned with the constituent in terms of voting orientations. An increase in *political misalignment* means that Representative has become less aligned with the constituent in terms of *voting orientation*. Again, β_2 is our difference-in-differences estimator that captures the adoption's effect on *political misalignment* between the Representatives and their constituents. A positive and significant value for β_2 means that the Representatives became less aligned with their constituents after the adoption and a negative and significant value for β_2 means that the Representatives became more aligned with their constituents in terms of voting orientations.

5. Results

For model-free evidence, Table 3 provides a comparison between the adopters and non-adopters before and after their adoption of Twitter. Compared to non-adopters, eventual adopters had much lower mean *voting orientation* before they adopted Twitter (0.484 vs 0.386). However after the adoption, the adopters had a higher mean *voting orientation*. That is, adopters became more conservative after joining Twitter.

Table 3. Comparison of Means between Eventual *adopter*s And Non-adopters

Variable	Period	*adopter*	Non-adopter
Representatives' voting orientation	Before adoption (*twitter status*=0)	0.386	0.484
	After adoption (*twitter status*=1)	0.572	
Constituents' voting orientation	Throughout 111th Congress	0.606	0.624
Political misalignment	Before adoption (*twitter status*=0)	0.238	0.231
	After adoption (*twitter status*=1)	0.179	

According to Table 3, 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 at all during the 111th Congress had a slightly higher mean *voting orientation* (0.624) meaning that the adoption of Twitter by Representatives from less conservative districts was slightly higher than that of Representatives from more conservative districts. Among the adopter districts, the *political misalignment* becomes 14.1% smaller after the adoption.

Table 4 reports our estimation results. Model 1 reports the results based on fixed effects specification with instrumental variables using two-stage least-squares (2SLS). 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 *adopter* × *twitter status* which reflects the average effect of the adoption on the adopter group is significant and positive. According to Model 1, adopters' voting orientation increases by 9.1 percentage points after the adoption. Since *adopter* does not vary over time, the coefficient for this variable in Models 1 and 4 are dropped. Model 2 reports the results of the Ordinary Least Squares (OLS) model with 2SLS specification. *Adopter* has a negative and significant coefficient meaning that, before the adoption, the eventual adopters had a lower *voting orientation* (more liberal) than did the non-adopters. The coefficient for the interaction term is significant and positive indicating that the eventual adopters' *voting orientation* shifts toward the conservative spectrum after the adoption by 18.8 percentage points.

Model 3 reports the results with the zero-one inflated beta distribution (ZOIB) specification.[5] The reason for using this specification is that both *voting orientation* and *political misalignment*'s range of values is bounded. That is, *voting orientation* and *political misalignment* are only allowed to vary from 0 to +1. Since the OLS specification assumes a normal distribution, the linear specification may not work well in this setting. According to Kieschnick and McCullough (2003), parametric regression models based on beta distribution are recommended for these data. Particularly, the ZOIB model has been adopted in

[5] The model was executed in STATA using the user-generated module ZOIB (Buis 2010b).

political science literature when WNOMINATE scores were employed to construct the outcome variable (Burmester and Jankowski 2014). The ZOIB model consists of three separate regression models: 1- a logistic regression model for whether or not the proportion equals 0, 2- a logistic regression model for whether or not the proportion equals 1, and 3- a beta regression model for the proportions between 0 and 1 (Buis 2010a).

For model 3 in Table 4, both the coefficients and their marginal effects are provided. The coefficient for *adopter* is significant and negative indicating that the adopters were more liberal than the non-adopters by an average of 0.078 points. The interaction between *adopter* and *twitter status* is significant and positive. After adopting Twitter, Representatives become almost 0.15 points more conservative according to the marginal effect in model 3.

The outcome variable in Models 4 to 6 is *political misalignment*. Similar to Model 1, Model 4 reports the results of FE/2SLS specification. The coefficient for the interaction term is negative and significant. According to this result, Representatives who adopted Twitter during 111^{th} Congress became 0.01 point more aligned with their constituents. Given that the mean *political misalignment* is 0.211 (Table 1), 0.01 point change corresponds to approximately 5% more alignment. Model 5 reports the results based on OLS/2SLS regression. This model does not reveal any significant difference in *political misalignment* between eventual adopters and non-adopters prior to the adoption. However, the interaction term is significant and negative. On average, the *political misalignment* for a Representative decreases by 0.039 points after he/she adopts Twitter. Model 6 reports the results of ZOIB model. Again, based on this model the adopters and non-adopters do not have a significant difference in terms of *political misalignment* before the adoption by adopters. On the other hand, the coefficients and the marginal effects are both negative and significant for the interaction term. According to the marginal effects, Representatives who adopt Twitter further align with their constituents by 0.046 points.

We employed Eicker-Huber-White robust standard errors in models 2, 3, 5, and 6. We also included dummies for each month from January 2009 to December 2010 to control for changes in overall shifts in Representatives' voting behavior. The error terms in models 2, 3, 5, and 6 are clustered at the Representative level to account for autocorrelation in the data across Representatives and over time (Bertrand et al. 2004). To check the robustness of our findings, we also removed those Representatives who adopted Twitter prior to January 2009 and then replicated our analysis for the new sample. We further allowed time interactions by treated and control groups and replicated the analysis. The results were not significantly different from the results presented in table 4.[6]

Table 4. Impact of Twitter on *Voting orientation* and *political misalignment*

	(DV= *voting orientation*)				(DV=*political misalignment*)			
	Model 1 (2SLS)	Model 2 (2SLS)	Model 3		Model 4	Model 5	Model 6	
			Coefficient	Marginal Effect			Coefficient	Marginal Effect
adopter		**-0.101*** (0.010)**	**-0.329*** (0.032)**	**-0.078*** (0.007)**		-0.007 (0.679)	0.027 (0.072)	0.004 (0.012)
adopter × twitter status	**0.091*** (0.007)**	**0.188*** (0.012)**	**0.630*** (0.034)**	**0.151*** (0.008)**	**-0.010** (0.002)**	**-0.039** (0.011)**	**-0.278*** (0.059)**	**-0.046*** (0.009)**
Controls		√	√			√	√	
Robust		√	√			√	√	
Time-fixed effects	√	√	√		√	√	√	
Clustered at Representative level		√	√			√	√	
Instruments	√	√			√	√		
Adj. R-squared	0.490	0.160			0.228	0.136		
N	10537	10537	10537		10537	10537	10537	
F-statistic Prob > F	8140.87 <0.001	2175.15 <0.001			115.61 <0.001	1433.78 <0.001	326.52 <0.001	
Specification	FE/2SLS	OLS/2SLS	ZOIB		FE/2SLS	OLS/2SLS	ZOIB	

Note 1: We employed Eicker-Huber-White robust standard errors.
Note 2: Within panel R-squared is reported in FE models.
Note 3: First-stage estimates for instrumental variables are reported in Appendix B.
Note 4: Wald Chi2 instead of F-statistic is reported for ZOIB models.
Note 5: In ZOIB models, the size of the coefficients are not interpretable. Therefore, marginal effects are reported and should be used for interpretation. Marginal effects for *adopter* and *adopter × twitter status* represent the percentage point changes in the proportions by shifting from the control group to the treatment group.
* Significant at 0.05, ** Significant at 0.01, *** Significant at 0.001

[6] Due to the similarity of the results with those in table 4, we did not report them here. But they can be provided upon request.

We next examine the effect of Twitter use on the *Representatives' voting orientations*. Since the use of Twitter by adopters could be heterogeneous (for instance some of the Representatives may not actively use Twitter after they create the accounts), we use the log number of tweets posted by the Representatives during each month (*tweets frequency*) as an indicator for use and run two models with FE specification to study the relationship between Twitter use and *voting orientation* and *political misalignment*. 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 posted by Representatives is associated with a) more conservatism and b) better political alignment with constituents.

Table 5. Impact of Twitter on *Voting orientation* and *political misalignment*

	(DV= *voting orientation*) Model 7	(DV=*political misalignment*) Model 8
tweets frequency (logged)	**0.010*** **(0.004)**	**-0.006*** **(0.002)**
Robust	√	√
Time-fixed effects	√	√
Individual-fixed effects	√	√
R-squared (within)	0.471	0.198
N	10537	10537
F-statistic Prob > F	287.78 <0.001	79.89 <0.001
Specification	FE	FE

Note: We employed Eicker-Huber-White robust standard errors.
*** Significant at 0.001

We also used the number of tweets in which the Representatives' Twitter handles (*handle-mentions frequency*) were mentioned on Twitter in any given month as an indicator for constituents' use of Twitter.[7] According to table 6, the coefficient for *handle-mentions frequency* is positive and significant in model 9

[7] It is worth noting that we were unable to determine which tweets were from which Congressional district. Therefore, it is not clear if the tweet was indeed from the 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.

and negative and significant in model 10. The latter indicates that the Representatives who are mentioned more frequently on Twitter sphere, tend to be more aligned with the constituents.

Table 6. Impact of Twitter on *Voting orientation* and *political misalignment*		
	(DV= *voting orientation*) Model 9	(DV=*political misalignment*) Model 10
handle-mentions frequency (logged)	**0.012***** **(0.001)**	**-0.005***** **(<0.001)**
Robust	√	√
Time-fixed effects	√	√
Individual-fixed effects	√	√
R-squared (within)	0.008	0.001
N	10537	10537
F-statistic Prob > F	72.18 <0.001	15.96 <0.001
Specification	FE	FE

Note: We employed Eicker-Huber-White robust standard errors.
*** Significant at 0.001

5.1. Addressing the Selection Bias

The Representatives' decision of adopting Twitter can be correlated with their *voting orientation*. For instance, it could be that those Representatives who decide to be more aligned with their constituents also decide to establish a new communication channel with them. Therefore, the decision for adoption Twitter (or selecting to be in 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 be correlated with the decision to adopt Twitter. These time-variant unobservables could lead, for example, to different trends over time for adopters and non-adopters. One way to address this issue would be to employ time-variant instrumental variables. However, the instrumental variables approach that we have undertaken to address the selection problem relies on validity of the instruments. Because we are unable to empirically test the exogeneity of the instrumental variables, we employ a variety of methods in the following section to address the selection bias.

5.1.1. Propensity Score Matching

One of the methods for evaluating the potential selection effects is propensity-score matching (PSM) approach (DiPrete and Gangl 2004; Leuven and Sianesi 2014; Sun and Zhu 2013). The instrumental variable approach and the propensity-score matching 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. Propensity-score matching corrects for selection bias by matching adopters with non-adopters based on observables. Under propensity-score matching scheme, we used Representative's age, gender, seniority in Congress, percentage of party-favored votes, number of sponsored bills, number of co-sponsored bills, percent of missed votes, voting orientation[8], constituent's mean household income, percent of high school graduates, percent of white population as attributes to be matched upon. Table 2 provides the descriptions and summary statistics for these variables.

Since the PSM method requires one pre-event and one post-event observation for each subject, and since Representatives created their Twitter accounts in different months of the study, we run our model for each month during which at least ten Representatives adopted Twitter. For each month[9] we first collapse each of our outcome variables, y_{it} , into simple averages before and after that month for each Representative i, and denote these averages as y_i^{pre} *and* y_i^{post}. Then for each month, we run a Difference-in-Difference model that compares the changes ($\Delta y_i = y_i^{post} - y_i^{pre}$) in *voting orientation* of Representatives who adopted Twitter during that month with matched Representatives who never adopted Twitter during The 111th Congress. It is worth noting that along with the time invariant variables we used for matching, we also include y_i^{pre} for matching. This would help us to compare the Representatives whose *voting orientation* scores were similar before the adoption. For each month, the PSM matches every adopter

8 The *voting orientation* in this case is y_i^{pre} which will be described later.

9 Excluding the first month (January 2009). The reason is that Representatives' *voting orientation* is not observed prior to this period.

with one similar non-adopter. Then using a logit model, we compare Δy_i for adopters and similar non-adopters for each month.

Figure 4 shows the number of adopters during each calendar month. According to Figure 4, the majority of the Representatives created their accounts in the first year of 111th Congress. Table 7 reports the results of the difference-in-difference estimates under the propensity-score matching scheme.

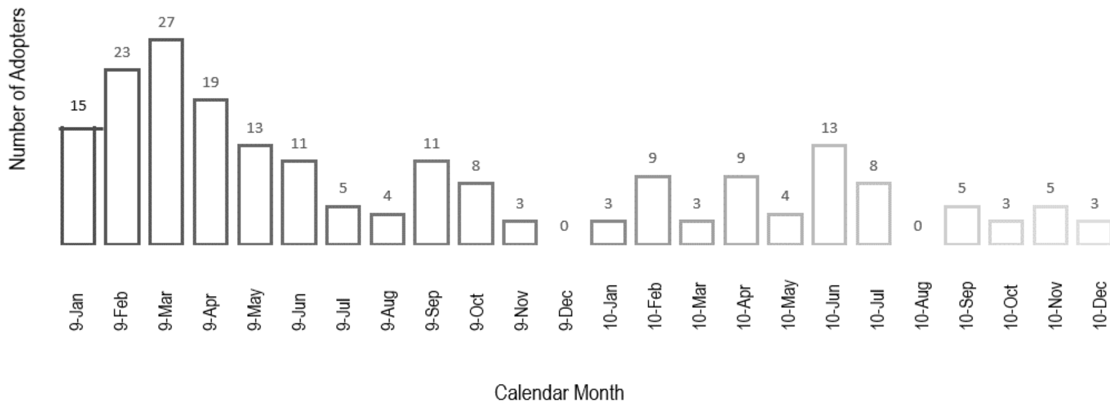

Figure 4. The Frequency of *adopter*s during Each Calendar Month

Table 7. PSM Estimates			
Calendar Month	Model 13 $\Delta y_i =$ Changes in *voting orientation*	Model 14 $\Delta y_i =$ Changes in *political misalignment*	Number of *adopter*s
Feb-09	0.075** (0.021)	-0.045** (0.009)	23
Mar-09	0.067* (0.20)	-0.062** (0.018)	27
Apr-09	0.031* (0.013)	-0.031* (0.011)	19
May-09	0.0003 (0.019)	-0.069* (0.026)	13
Jun-09	0.063** (0.018)	0.058 (0.067)	11
Sep-09	0.052** (0.015)	-0.055** (0.011)	11
Jun-10	0.034* (0.017)	-0.137*** (0.018)	13

Note 1: Robust standard errors are reported in parenthesis.
Note 2: Logit model was used for estimations.
Note 3: At least one Representative from Non-adopter group was matched for every adopter at each month.
* Significant at 0.05, ** Significant at 0.01, *** Significant at 0.001

Twitter status estimates in Model 13 remains positive and statistically significant for every month except for May 2009. The impact of Twitter adoption on changes in *voting orientation* ranges from 0.031 points to 0.075 points. The impact of Twitter adoption on changes in *political misalignment* remains negative and significant for every month except for June 2009. The impact of Twitter adoption on changes in *political misalignment* ranges from -0.031 to -0.137.

5.1.2. External Events

Along with instrumental variable and propensity score matching techniques, we further address the potential endogenity of Twitter adoption by narrowing down the sample to only those who created their Twitter account during the month of June 2010. The reason is that in 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 more than 71% of them use iPhone (Hattem 2014) [10], we believe that this external event may have motivated some of the Representatives to start using Twitter. Particularly, June 2010 had the highest number of adopters in the second half of the Congress and the decision of creating a social media account due to the availability of the app for mobile devices is unlikely to be correlated with the changes in Representatives' *voting orientation*. 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 interaction term is significant and positive for *voting orientation* and significant and negative for *political misalignment*, confirming our previous findings. The effect of Twitter adoption on *voting orientation* according to the marginal effects is 0.060 points increase. The magnitude of the effect for *political misalignment* is about

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

the same as the previous results. On average, a Representative who adopted Twitter in June 2010 becomes 0.033 points more aligned with the constituent after the adoption.

Table 8. Impact of Twitter on *Voting orientation* and *political misalignment* (June 2010 *adopters*)

	(DV= *voting orientation*)				(DV=*political misalignment*)			
	Model 15	Model 16	Model 17 Coefficient	Model 17 Marginal Effect	Model 18	Model 19	Model 20 Coefficient	Model 20 Marginal Effect
adopter		**-0.139*** (0.015)**	**-0.500*** (0.053)**	**-0.120*** (0.013)**		0.008 (0.032)	0.131 (0.150)	0.023 (0.026)
adopter × *twitter status*	**0.062*** (0.013)**	**0.066** (0.024)**	**0.252** (0.091)**	**0.060** (0.022)**	**-0.025* (0.011)**	-0.026 (0.018)	**-0.190* (0.081)**	**-0.033* (0.014)**
Controls		√	√			√	√	
Robust	√	√	√		√	√	√	
Time-fixed effects	√	√	√		√	√	√	
Clustered at Representative level		√	√			√	√	
Adj. R-squared	0.534	0.156			0.333	0.142		
N	312	4920	4920		312	4920	4920	
F-statistic Prob > F	211.82 <0.001	54.64 <0.001	958.44 <0.001		77.69 <0.001	10.234 <0.001		
Specification	FE	OLS	ZOIB		FE	OLS	ZOIB	

Note 1: We employed Eicker-Huber-White robust standard errors.
Note 2: Within panel R-squared is reported in FE models.
Note 3: Wald Chi2 instead of F-statistic is reported for ZOIB models.
Note 4: In ZOIB models, the size of the coefficients are not interpretable. Therefore, marginal effects are reported and should be used for interpretation. Marginal effects for *adopter* and *adopter* × *twitter status* represent the percentage point changes in the proportions by shifting from the control group to the treatment group.
* Significant at 0.05, ** Significant at 0.01, *** Significant at 0.001

5.1.3. Twitter Usage & *political misalignment*

If indeed the adoption of Twitter by Representatives influences their decisions in favor of the constituents, it is expected that in geographic regions where citizens use Twitter more often the magnitude of the influence to be larger. Therefore, we collected data about per capita usage of Twitter per state[11] to

[11] It is worth noting that the district level data could not be obtained. Therefore we used data from http://blog.hubspot.com/blog/tabid/6307/bid/7905/Twitter-Usage-Per-Capita-How-States-Compare-Infographic.aspx which represents a transformed measure for overall Twitter usage per capita for each state. The data in this source is based on the overall Twitter usage in 2010.

compare the influence of Twitter adoption on *political misalignment* across the states. Among the 50 states, Mississippi had the lowest per capita Twitter usage score. Massachusetts had the highest per capita Twitter usage score. Since this data is at state level, we averaged the district level *political misalignment*s for each state and then ran a regression model with state-level *political misalignment* as the dependent variable and Twitter usage and control variables[12] as the regressors. The coefficient for Twitter usage was -0.039 ($p<0.001$), revealing that the *political misalignment* is smaller in states where Twitter is used more. This finding confirms our prior findings about the role of Twitter adoption on *political misalignment*.

5.2. Addressing the Bias due to Serial Correlation

Since the Difference-in-Difference (DD) coefficients in this study rely on many month 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 two methods:

5.2.1. Ignoring Time Series Information

According to (Bertrand et al. 2004), collapsing the time series information into a "pre" and "post" period produces consistent standard errors and is an effective correction for the inconsistent standard errors due to serially correlated outcomes. To construct collapse *voting orientation*, we calculate Representative i's simple average *voting orientation* before the adoption (y_i^{pre}) and after the adoption (y_i^{post}). Similarly, we obtain the value for the *political misalignment* before the adoption (y_i^{pre}) and after the adoption (y_i^{post}) by taking the simple average of *political misalignment* before and after adoption. According to Table 9, the

[12] Constituents' scores, household income, unemployment rate, and % highschool graduates were used as control variables.

results in both models confirm our previous findings. The impact of Twitter adoption on mean *voting orientation* is positive and significant (0.071 points increase in mean *voting orientation*) and its impact on mean *political misalignment* is negative and significant (almost 0.040 points decrease in misalignment).

Table 9. Impact of Twitter on Mean *voting orientation* and Mean *political misalignment*		
	(DV=Mean *voting orientation*) Model 21	(DV=Mean *political misalignment*) Model 22
adopter × twitter status	**0.071*** (<0.001)**	**-0.039*** (<0.001)**
Robust	√	√
Time-fixed effects	√	√
R-squared (within)	0.449	0.207
N	10537	10537
F-statistic Prob > F	331.11 <0.001	106.57 <0.001
Specification	FE	FE

Note: We employed Eicker-Huber-White robust standard errors.
*** Significant at 0.001

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 to compute the standard error for a specific experiment, the difference-in-difference estimates for a large number of randomly generated placebo laws are estimated first. Then the empirical distribution of the estimated effects for these placebo laws are used to form significance test for the true law. In our case, we start with estimating the difference-in-difference estimate (β_2 in specification 1) using the observed data. The next step is to generate the placebo data for many times and run the model in specification 1 on this placebo data. We decided to create 10,000 placebo data sets. To create each placebo data, we randomly draw 204 Representatives[13] from all of the Representatives in our data and allow

[13] Since there are 204 actual Representatives who adopted Twitter during 111th Congress, we matched that in our simulation to create the placebo data.

each of them to randomly pick a month to adopt Twitter. We then run a model with specification 1 on this placebo data and obtain the difference-in-difference coefficient. Repeating this procedure for 10,000 times results in 10,000 difference-in-difference estimates.[14] The next step is to compare the actual difference-in-difference estimate in the first 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 identify the placebo difference-in-difference estimates at the 0.025 lower and upper tail of the distribution and use these values as cutoffs: If the actual difference-in-difference estimate lies outside these two cut-off values, we reject the hypothesis that it is equal to 0, otherwise we accept it. Table 10 reports the results of this procedure for both *voting orientation* and *political misalignment*.

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
adopter × twitter status	**0.022**	-0.012	0.012	**-0.010**	-0.009	0.010
Time-fixed effects	√	√	√	√	√	√
Individual-specific effects	√	√	√	√	√	√
Specification	OLS	OLS	OLS	OLS	OLS	OLS

According to Table 10, both actual difference-in-difference estimates for *voting orientation* and *political misalignment* lie outside 95% distribution of the placebo estimates. For *voting orientation*, the actual difference-in-difference estimate is larger 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 smaller than the lower bound. That is, the effect of adoption on *political misalignment*

[14] To perform Randomization Inference with Temporal Dependencies, we wrote a script in R. The code will be available from the corresponding author upon request.

is negative and significant at 0.05. The results in Table 10 confirms the previous results about the effects of Twitter adoption on *voting orientation* and *political misalignment*.

5.3. Representative-specific & Constituent-specific Effects

To elaborate more 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. 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 Representative i's party affiliation matches with the constituent's party affiliation, and 0 otherwise. According to Table 11, those Representatives who represent an opposing party's district use Twitter more effectively to get closer to their constituents. Their *political misalignment* reduces slightly above 2.6 times more than that of the other Representatives whose party affiliation matches their constituent's party affiliation. In other words, a Republican Representative who is elected in a Democrat district or a Democrat Representative who is elected in a Republican district uses Twitter to reduce the misalignment with their constituents more so than Representatives who represent their own party district. This could be due to the fact that these Representatives feel more pressure from the constituent and are more sensitive to what they share on Twitter. We also found that Democrat Representatives' *voting orientation* scores increase more than their Republican peers after joining Twitter. Democrats, however, get closer to the constituents as they join Twitter more than Republicans do. *Age, seniority, and sponsorship* did not impact the relationship between adoption and *Voting orientation* or misalignment. Those representatives who co-sponsored more bills during the 111^{th} Congress became more conservative after joining Twitter. *Co-sponsorship* does not influence the effect of Twitter adoption on *political misalignment*. The number of bills missed by Representatives is associated with neither *voting orientation* nor *political misalignment*. Those Representatives who follow their Party in voting in Congress more than others, tend to become further conservative after joining Twitter. The literacy level of the constituent seems to be negatively related to shifting toward conservatism. Yet, does not have any effect on *political misalignment*. Surprisingly, in districts were the average household income is higher, the adoption of Twitter by Representative is less impactful in moving closer to the constituent. Unemployment rate in Congressional district does not influence the effect of Twitter adoption on *political misalignment*.

Table 11. The Effects of Moderating Factors on *Voting orientation* and *political misalignment*

	Adoption effect on *Voting orientation*	Adoption effect on *political misalignment*
Representative & constituent party match =1	N	+
party affiliation = Republican	-	+
age	N	N
seniority	N	N
sponsorship	N	N
co-sponsorship	+	N
missed votes (%)	N	N
party votes (%)	+	-
white (%)	-	N
highschool graduates (%)	-	N
household income (logged)	-	+
unemployment rate (%)	+	N

Note 1: FE specification is used in all of the models. We interacted each factor with *twitter status* in Specification 1.
Note 2: 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.
Note 3: 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.

6. Discussion

Social network theory suggests that a social network user's initial opinion or behavioral assessment might change due to the information obtained from the OSNs (Friedkin 1998). Furthermore, by communicating and interacting with one another, people create social influences that affect their opinions, attitudes, and behaviors (Fang et al. 2013; Iyengar et al. 2011). For politicians, an online social network such as Twitter allows them to better interact with their constituents. After all, politicians are representing their constituents and need to be familiar with their political preferences when making decisions in the Congress. Since OSNs enable citizens to share their political views and preferences and the issues they face in their communities, these platforms contain useful information for politicians. Although Twitter data is public and available to everyone, politicians who create their account and actively engage in Twitter would have a higher chance of observing citizens' discussions on Twitter. More importantly, politicians' activity on Twitter may cause social and political mobility among the constituents. According to Bond et al. (2012), based on a study of millions of Facebook users on 2010 Election Day, political messages in OSNs have a measurable effect on political self-expression, information seeking and real-world voting behavior of millions of people. Furthermore, the messages not only influenced the users who received them but also the users' friends, and friends of friends. Politicians, by engaging in online discussions in OSN platforms, can inform the citizens about their own political stances and their peers' activities in the Congress. This direct and convenient way of communication with its broad reach was not available to the politicians before the proliferation of OSNs. OSNs provide the politicians with a new channel that not only keeps the town hall attenders engaged, but also reaches out to less-politically active citizens and mobilize them.

Furthermore, according to tables 5 and 6, not only being present on Twitter would be influential in *voting orientation* and *political misalignment*, but also the extent to which the Representatives (Table 5) and constituents (Table 6) use Twitter for political communication would be influential in *voting orientation* and *political misalignment*. In this perspective, OSNs can provide politicians with information about less politically-active constituents and therefore a more representative sample of the constituents and their preferences. Due to these effects of OSN platforms on political involvement, as evidenced by our results, the adoption of OSNs by politicians may help them to be further aligned with their constituents. Figure 5 provides a good example of this effect. According to Figure 5, which is based on Representative Stephanie Sandlin (D-SD 1) and her constituent's political ideology, Representative Sandlin was far away from the constituent before adopting Twitter. After the adoption, her voting orientation moved closer to the political ideology of her constituent.

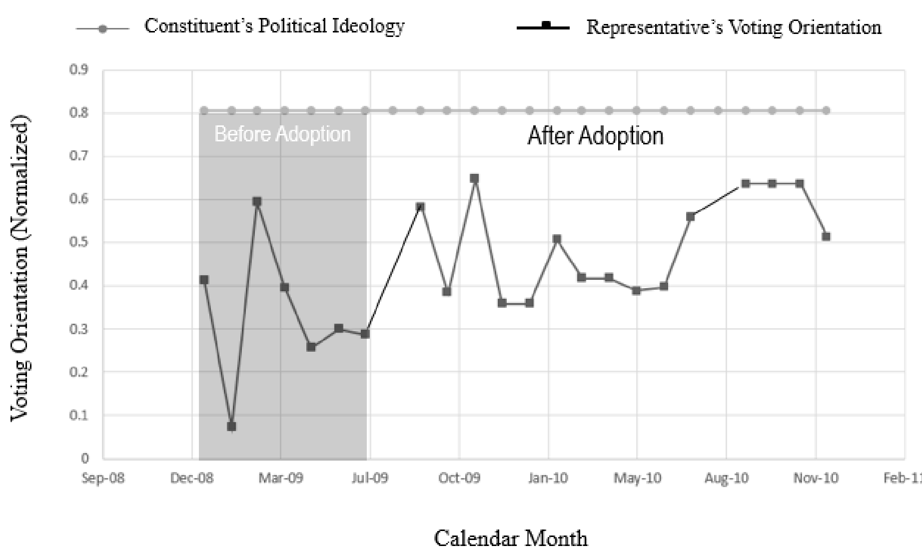

Figure 5. Changes in *voting orientation* of Representative Stephanie Sandlin (D-SD 1).

In this study we also find that Representatives' presence in Twitter platform directs them toward the conservative side of the *voting orientation* spectrum. At the same time, their voting orientations become more aligned with their constituents. Figure 6 shows the before and after change in Representatives' voting orientations relative to their constituents' political preferences. It shows that, although the politicians became more conservative after the adoption, their average *voting orientation* has shifted toward the middle of the spectrum, which signals a more moderate *voting orientation* after the adoption. The comparison between the mean *voting orientation* of the constituents with that of the adopters shows that the

Representatives who adopted Twitter during the 111th Congress moved closer to their constituents in terms of *voting orientation*.

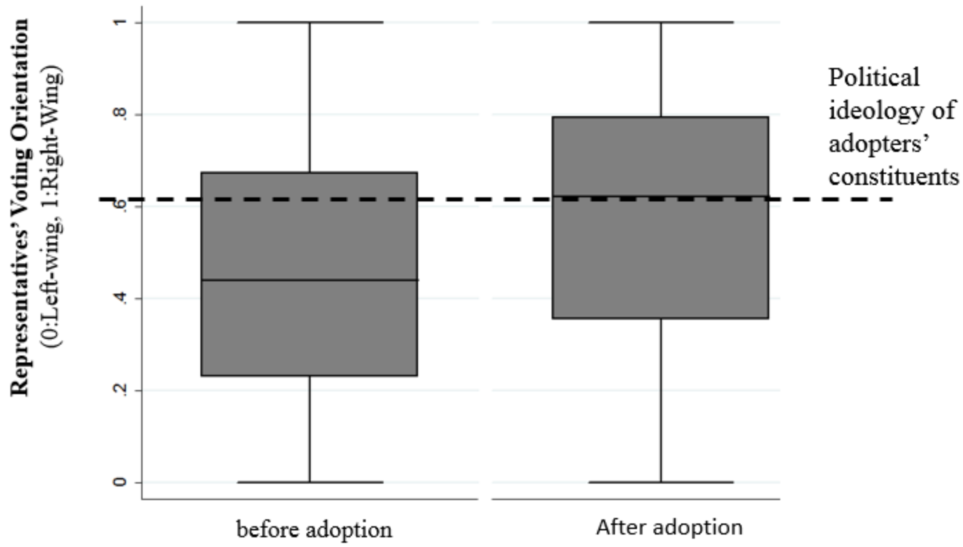

Figure 6. The Impact of Twitter Adoption on *Voting orientation* of Representatives Who Joined Twitter during The 111th Congress (The dashed line represents the political ideology of adopters' constituents).

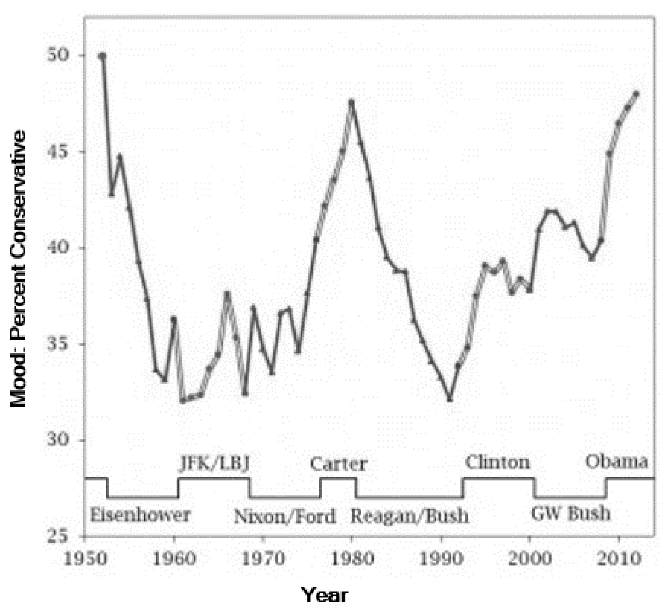

Figure 7. Americans' Conservative Policy Mood (Bartels 2013)

It is worth mentioning that although we do not have an estimate for political ideology of Twitter users, studies show that Americans at large deviated from liberalism and became more conservative during the time period of The 111th Congress (Bartels 2013; Stimson 2013). Figure 7 shows the trend of the conservatism policy mood among Americans since 1950. According to this plot, Americans' conservative policy mood was on the rise during the time period of The 111th Congress. This is in line with our data set that shows a higher conservatism in Congressional districts during The 111th Congress.

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 tapped. To study the impact of online social media on the voting behavior 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 datasets. We collected Representatives' data including their voting records, Twitter data, and the constituents' data. Using fixed effects and difference-in-difference approaches, our analysis revealed that the adoption of Twitter by directs them toward the conservative side of political spectrum. Furthermore, we found that the adoption of Twitter by Representatives helps them to get closer to the political ideology of their constituents and therefore better represent them in Capitol Hill.

Although the underlying mechanism of influence of Twitter adoption on *voting orientation* and *political misalignment* are not studied in this paper and this shall be regarded as a limitation of this study, we suggest that the use of the new media by politicians and constituents may have a two-folded effect:

1- Effect of politicians on constituents: Using these platforms, the politicians could inform the constituents about their political undertakings in Capitol Hill. Although the majority of the politicians could also use traditional forms of media (such as national and local media and town hall meetings) to communicate with the public, those who use OSN platforms would also get the chance to communicate with those citizens who do not use traditional media as sources of information. As Senator Josh Stein (D- NC) put it: "[social media] is a great way for people who don't have the time to be able to spend following the ins and outs of issues and legislative battles to get a quick first-person account of what's been going on in the legislature and state government." (Jeffries 2014) Moreover, the politicians' engagement in OSNs could mobilize the town hall attenders even further by giving them the opportunity to openly discuss their views on local, national, and international issues.

2- Effect of constituents on politicians: With the use of OSNs, the constituents could initiate dialogue with their Representatives and let them know about their social and political preferences. The transparency and broad reach of OSNs would encourage the constituents to conveniently and publicly discuss the issues with their Representatives. That is, requests directed at politicians through OSN platforms are public and available to other members of the community. The traditional media (e.g. phone calls, town hall meetings, and letters) would not have the same transparency or broad reach. The transparency and broad reach of the OSNs may also motivate other citizens (or local and national media) to join the petitions. The politically involved citizens who engage in town hall meetings and communicate with their Representatives through traditional media such as phone calls and letters, would find OSN platforms useful in mobilizing less-politically active citizens to influence the politicians even further. There are thousands of social media campaigns organized by voters who demand a specific vote on a bill or propose new bills to Representatives.

Overall, OSN platforms provide the constituents with a convenient channel to be heard by the politicians. Particularly, those constituents who are not politically active (i.e. those who don't attend the town hall meetings and do not follow the news in the local and national media) would be mobilized by the Representatives and politically active constituents through OSN.[15]

Figure 9. A Tweet Addressed to John Carter (R- TX 31)

Another limitation of this study is related to the sample. U.S. Representatives are elite politicians whose decision making in politics would differ from regular citizens. Thus, generalizability of these findings could be limited. We also note that the similarity of the names between some of the Representatives and other users could distort the accuracy of *name-mention tweets* collected from Twitter. 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 a potential high accuracy for *name-mention tweets*.

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[15] In a separate study we found that Representatives who adopted Twitter by the end of The 111th Congress had a higher chance for being re-elected in The 112th Congress. We studied the impact of Representatives' social media adoption on the results of the next election by collecting data about Twitter, Facebook, and Youtube adoptions by Representatives. After controlling for a number of Representative-specific and constituent-specific factors, we found that Twitter and Facebook adoption are positively associated with the probability of Representative being elected for the next term. Youtube adoption however, did not yield any significant results. The results of this study will be reported and discussed in a separate paper.

Another limitation with regard to *name-mention tweets* and *handle-mention tweets* is that we don't know if these tweets were sent by the constituents. However, we argue that this information is not available to the Representatives for the most part. We also recognize that, if available, the Representatives may weigh the tweets posted by their own constituents more than other tweets. Last but not least, a dynamic monthly measure for constituents' political ideology could have helped us to construct a more accurate measure for *political misalignment*. However, to our best knowledge, all of the measures developed for constituents' *voting orientation* are for four years or longer time periods, as these measures are developed, at least partly, based on the presidential elections data or national survey data administered over the years (Kernell 2009; Tausanovitch and Warshaw 2013).

To better extend the realm of this research, one may study the dynamic network of politicians in social media. Such network can be built based on friendships or conversations in online social networking platforms. A dynamic network analysis may shed more light on the underlying mechanism that causes the change in *voting orientation*. Moreover, we only extracted and analyzed data from Twitter platform due to its popularity in political domain. A good extension of this study would be studying the impact of adoption of other OSN platforms by politicians on their *voting orientation*. Although Twitter is sometimes perceived as a broadcasting medium rather than a social network, it shares certain features with other OSN platforms. For instance, Twitter enables the users to follow and be followed by others. Or, a Twitter user only receives the tweets from her following list on her home page. While some users might decide to only broadcast their own ideas, prior studies show that Twitter users read tweets posted by people they follow. For instance, a study by Liu and colleagues (2014) shows that during The 111th Congress (from January 2009 to December 2010), more than 30% of the posts on Twitter were either replies or retweets. Twitter also recommends out-of-network users based on the current network of followers/ followings. Replicating this study in other OSN platforms with a different set of features may enable the researchers to examine information-richness of the networks and thus elaborate on the mechanisms of influence on greater detail.

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Appendix A: Estimating WNOMINATE Scores

To estimate WNOMINATE scores for Representatives, we employed a software package designed to estimate Poole and Rosenthal WNOMINATE scores in R. According to Poole et al. (2011), WNOMINATE assumes probabilistic voting based on a spatial utility function, "where the parameters of the utility function and the spatial coordinates of the legislators and the votes can all be estimated on the basis of observed voting behavior." (p. 1) One of the key inputs of this program is the roll call matrix for The 111th House of Representatives. The roll call matrix is the result of two sets of variables: an ideal point for each Representative that stands for their ideology or vote preference, and separate Yea and Nay locations for each roll call. It is assumed that the Representatives have an ideal point on each of these two dimensions. As explained in Poole and Rosenthal (2007) and widely used in political science literature (Aldrich and Battista 2002; Aldrich et al. 2014; Lupu 2013), the first dimension can be interpreted as the Liberal-Conservative spectrum. The second dimension picks up social issues such as civil rights for African-Americans in 1960s. According to McCarty et al. (2008), this dimension is no longer important. Therefore, the estimates on the first dimension were used in our study.

Since we need WNOMINATE scores for each Representative during each month, we created roll call matrices with Representatives' votes cast during each month of the study. Legislators who voted less than twenty times during each month were excluded from estimation and were treated as missing observations. Along with the roll call matrix WNOMINATE program requires other inputs, most of which are set by default as reported in (Poole et al. 2011). An important input that needs to be set is the argument "polarity", which is used to orient the results in the desired direction. The "polarity" is set by specifying a Representative to be positive in each of the two dimensions. Since researchers tend to orient Conservatives on the right and Liberals on the left, we identify one fiscally Conservative Representative (Republican Representative) to set the "polarity" on the first dimension and one socially Conservative Representative on the second dimension. We decided to use Representative Eric Cantor (R-VA 7th district) for the first dimension and Representative Walter Jones, Jr. (R-NC 3rd district) for the second dimension. The reason is that Representative Cantor has high score on the first dimension (fiscally Conservative) but low scores on the second dimension. In contrast, Representative Jones has low score on the first dimension but high scores on the second dimension (socially Conservative). Using these settings we estimated first dimension scores for each Representative for each month and used as a measure for voting orientation as reported in the manuscript.

Appendix B: Instrumental Variables Relevance

Table B provides first-stage estimation results for models 1, 2, 4, and 5 in Table 4 to illustrate the instrumental variable's relevance. In models B1 through B3 the instruments are separately introduced. In model B4, all three instruments are employed. We find that all of the instruments are highly correlated with becoming a Twitter adopter, and these results are statistically significant at the 5% level in all models. The overall Wald chi-squared test or *F*-test for the instruments in each model is also highly significant.

Table B. First-Stage Regressions And Instrument Relevance (DV = *adopter* × Twitter status)

	Model B1	Model B2	Model B3	Model B4
name-mentions frequency (logged)	**0.014****** **(0.005)**			**0.010**** **(0.003)**
committee effect		**0.015****** **(<0.000)**		**0.015****** **(<0.000)**
neighbor effect			**0.241**** **(0.085)**	**0.114*** **(0.060)**
Time-fixed Effects	√	√	√	√
Robust	√	√	√	√
Adj. R-squared (within)	0.205	0.691	0.207	0.691
N	10632	10680	10680	10632
F-statistic Prob > F	82.40 <0.001	69.81 <0.001	83.48 <0.001	68.98 <0.001
Specification	FE	FE	FE	FE

* Significant at 0.05, ** Significant at 0.01, *** Significant at 0.001