Representation, Homophily, and Polarization

in The U.S. House of Representatives in the Twitter Era

by

Seyedreza Mousavi

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Graduate Supervisory Committee:

Bin Gu, Chair
Ajay Vinze
Zhan Shi

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ABSTRACT

By collecting and analyzing more than two million tweets, U.S. House Representatives' voting records in 111th and 113th Congress, and data from other resources I study several aspects of adoption and use of Twitter by Representatives. In the first chapter, I study the overall impact of Twitter use by Representatives on their political orientation and their political alignment with their constituents. The findings show that Representatives who adopted Twitter moved closer to their constituents in terms of political orientation. By using supervised machine learning and text mining techniques, I shift the focus to synthesizing the actual content shared by Representatives on Twitter to evaluate their effects on Representatives' political polarization in the second chapter. I found support for the effects of repeated expressions and peer influence in Representatives' political polarization. Last but not least, by employing a recently developed dynamic network model (separable temporal exponential-family random graph model), I study the effects of homophily on formation and dissolution of Representatives' Twitter communications in the third chapter. The results signal the presence of demographic homophily and value homophily in Representatives' Twitter communications networks. These three studies altogether provide a complete picture about the overall consequences and dynamics of use of OSN platforms by Representatives.

DEDICATION

This dissertation is dedicated to my brilliant, loving and supportive wife, Gooya who has inspired me every day since we met. I also dedicate my dissertation to my parents Taleh Toluei and Ayat Mousavi who provided me with an environment to thrive, and to my parents in law Parvin Khosravi and Azizmohammad Goudarzi who always supported me.

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Chapter 1

THE IMPACT OF TWITTER ADOPTION ON LAWMAKERS' VOTING ORIENTATIONS

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 chapter studies this question in a unique context – the impact of U.S. Representatives' Twitter adoption on their voting orientations in The Congress. In particular, I consider whether the adoption of Twitter by Representatives makes them to vote more in line with the political ideology of their constituents. I constructed a panel data for 445 Members of the 111th U.S. House of Representatives across a period of 24 months. I 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, I found that the adoption of Twitter by Representatives makes them to vote more in line with their constituents. I 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.

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

1.1 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, Jaeger, & Grimes, 2010; Linders, 2012), and political campaigns (Bond et al., 2012; Wattal, Schuff, Mandviwalla, & Williams, 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% 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 & 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)

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, I use the U.S. Representatives' voting orientations to assess to what degree the public influences organizational decisions through OSN platforms. In particular, I examine whether the

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

adoption of OSNs moves politicians' voting orientations closer to the views of their constituents.

The organization of this chapter is as follows. Section 2 reviews the relevant literature. Section 3 presents This data, variables, and descriptive statistics. Section 4 discusses the empirical approach. Section 5 reports the results of the analyses. I discuss these findings and conclude with limitations and potential extension of this study in Sections 6 and 7.

1.2 Research Background

The IS literature has addressed a variety of societal issues including the digital divide (Riggins & Dewan, 2005), e-government services (Carter & Bélanger, 2005), political campaigns (Wattal et al., 2010), prevalence of HIV (Chan & 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, I propose that the adoption of OSNs by politicians can help them to vote more in line with the wish of their constituents.

1.3 Data

To study the impact of the adoption of Twitter on the voting orientation of politicians, I constructed a panel data for 445 Members of the 111th U.S. House of Representatives across a period of 24 months.

1.3.0.1 Dependent Variables

Spanning the 111th Congress, I estimate the monthly measure of Representatives' voting orientations based on votes cast by each Representative in a given month. I use Weighted Nominal Three-Step Estimation (WNOMINATE), a widely used estimation model in political science, for the estimation (Poole, Lewis, Lo, & Carroll, 2011).[1] WNOMINATE is "a scaling procedure that performs parametric unfolding of binary choice data." (Poole & 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

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

employed by political scientists to study the behaviors of the politicians based on their voting records (Aldrich & Battista, 2002; Aldrich, Montgomery, & Sparks, 2014; Lupu, 2013).

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

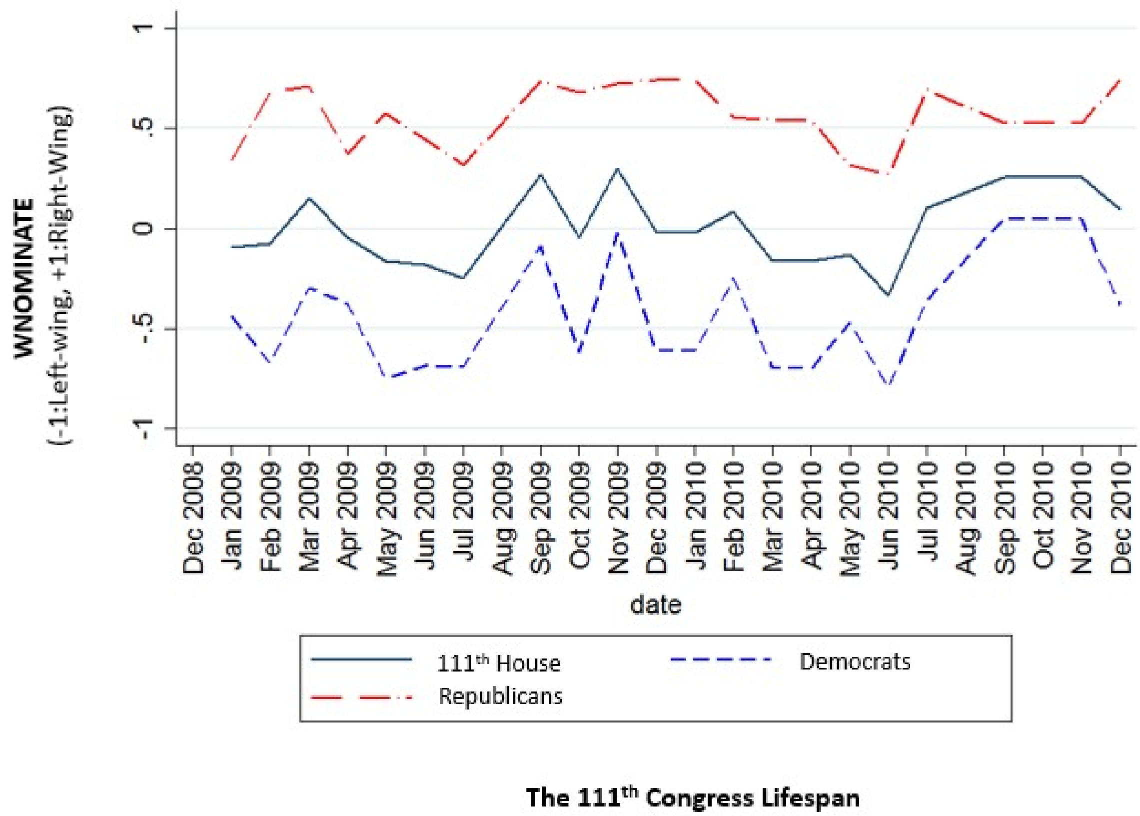

Figure 2. Average WNOMINATE scores for Members of 111th House of Representatives

1.3.1 Predictor and Control Variables

To capture the dates Representatives adopted Twitter, I 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, I 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, I 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.

I 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 1 provides the descriptions and the summary statistics for these variables.

1.3.2 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 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.

[2]The Representatives' retweets were removed from this data set and only the mentions were kept.

[3]I 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 I 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.

Table 1. Summary Statistics of Variables

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

Note: For months August 2009 and August 2010, the WNOMINATE scores were not estimated as the House of Representatives was in recess. I 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.

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

I 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. I

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

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. I 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. I 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, I 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.

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. I 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 2, 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. 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

1.4 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. I 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 & Ghose, 2014; Dranove, Kessler, Mcclellan, & Satterthwaite, 2003; Jin & Leslie, 2003; Sun & Zhu, 2013). I 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, I employ the following model:

$$y_{it} = \beta_0 + \beta_1 Q_i + \beta_2 Q_i \times x_{it} + \sum_{j=1}^{24} \gamma_j MonthDummy_j + \epsilon_{it} \tag{1.1}$$

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. I 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. I 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. I use Specification 1.1 to study the impact of Representatives' adoption of Twitter on two response variables (y_{it}). For the first response variable, I use Representatives' voting orientations (normalized WNOMINATE). β_2 is the 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 I use political misalignment. To construct political misalignment, I 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 the 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.

1.5 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.

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

Table 3. Comparison of Means between Eventual adopters 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	

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

Table 4 reports the 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.[4] 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 political science literature when WNOMINATE scores were employed to construct the outcome variable (Burmester & 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 111th Congress became 0.01 point more

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

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.

I employed Eicker-Huber-White robust standard errors in models 2, 3, 5, and 6. I 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 the findings, I also removed those Representatives who adopted Twitter prior to January 2009 and then replicated the analysis for the new sample. I 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.[5]

I next examine the effect of Twitter use on the Representatives' voting orientations.

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

Table 4. Impact of Twitter on Voting Orientation & Political Misalignment

	(DV= *voting orientation*)						(DV=*political misalignment*)					
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
					Coefficient	ME					Coefficient	ME
adopter			**-0.092*** (0.027)**	**-0.101*** (0.010)**	**-0.329*** (0.032)**	**-0.078*** (0.007)**			-0.002 (0.014)	-0.007 (0.679)	0.027 (0.072)	0.004 (0.012)
adopter × twitter status	**0.022*** (0.005)**	**0.091*** (0.007)**	**0.177*** (0.024)**	**0.188*** (0.012)**	**0.630*** (0.034)**	**0.151*** (0.008)**	**-0.010* (0.004)**	**-0.010** (0.002)**	**-0.047*** (0.011)**	**-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	0.490	0.161	0.160			0.228	0.228	0.135	0.136		
N	10537	10537	10537	10537	10537		10537	10537	10537	10537	10537	
F-statistic Prob > F	8002.36 <0.001	8140.87 <0.001	346.22 <0.001	2175.15 <0.001			115.32 <0.001	115.61 <0.001	25.32 <0.001	1433.78 <0.001	326.52 <0.001	
Specification	FE	FE/2SLS	OLS	OLS/2SLS	ZOIB		FE	FE/2SLS	OLS	OLS/2SLS	ZOIB	

Note 1: Eicker-Huber-White robust standard errors were employed.

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

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), I 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 the 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: Eicker-Huber-White robust standard errors were employed.

*** Significant at 0.001

I 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.[6] According to table 6, the coefficient for handle-mentions frequency is positive and significant in model 9 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.

[6]It is worth noting that I was 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, I argue that this information is mostly not available to the Representatives either.

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: Eicker-Huber-White robust standard errors were employed.

*** Significant at 0.001

1.5.1 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 I have undertaken to address the selection problem relies on validity of the instruments. Because I are unable to empirically test the exogeneity of the instrumental variables, I employ a variety of methods in the following section to address the selection bias.

1.5.1.1 Propensity Score Matching

One of the methods for evaluating the potential selection effects is propensity-score matching (PSM) approach (DiPrete & Gangl, 2004; Leuven & Sianesi, 2014; Sun & 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, I 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[7] , 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, I run the model for each month[8] during which at least ten Representatives adopted Twitter. For each month I first collapse each of the outcome variables, y_{it} , into simple averages before and after that month for each Represen-

[7]The voting orientation in this case is y_i^{pre} which will be described later.

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

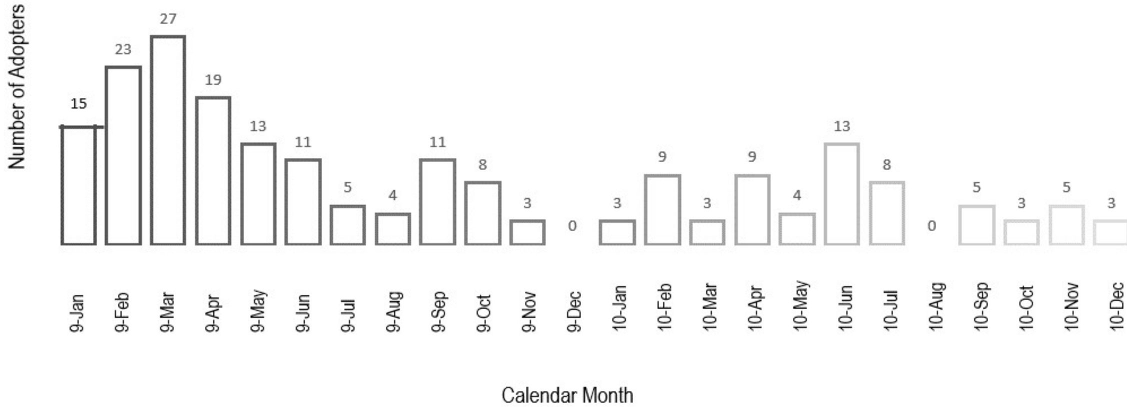

Figure 4. The Frequency of adopters during Each Calendar Month

tative i, and denote these averages as y_i^{pre} and y_i^{post}. Then for each month, I 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 I used for matching, I 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 with one similar non-adopter. Then using a logit model, I 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.

Twitter status estimates in Model 13 remains positive and statistically significant

Table 7. PSM Estimates

Calendar Month	Model 13 Δy_i = Changes in *voting orientation*	Model 14 Δy_i = Changes in *political misalignment*	Number of *adopters*
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

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.

1.5.1.2 External Events

Along with instrumental variable and propensity score matching techniques, I 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)[9], I 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 the 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 the 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 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.

1.5.1.3 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, I collected data about per capita usage of Twitter per state[10] to compare the influence

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

[10] It is worth noting that the district level data could not be obtained. Therefore I used data from http://blog.hubspot.com/blog/tabid/6307/bid/7905/Twitter-Usage-Per-Capita-How-States-

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: Eicker-Huber-White robust standard errors are reported in parenthesis.

Note 2: Within panel R-squared is reported in FE models.

Note 3: Wald Chi2 instead of F-statistic is reported for ZOIB models.

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

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, I averaged the district level political misalignments for each state and then ran a regression model with state-level political misalignment as the dependent variable and Twitter usage and control variables[11] as the regressors. The coefficient for Twitter usage was

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.

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

-0.039 ($p<0.001$), revealing that the political misalignment is smaller in states where Twitter is used more. This finding confirms the prior findings about the role of Twitter adoption on political misalignment.

1.5.2 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 I employ the following two methods:

1.5.2.1 Ignoring Time Series Information

According to (Bertrand, Duflo, & Mullainathan, 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, I calculate Representative i's simple average voting orientation before the adoption (y_i^{pre}) and after the adoption (y_i^{post}). Similarly, I obtain the value for the political misalignment before the adoption (y_i^{pre}) and after the adoption ($y_i^p ost)bytakingthesimpleaverageofpoliticalmisalignmentbeforeandafteradoption.AccordingtoTable$

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 1: Eicker-Huber-White robust standard errors are reported in parenthesis.
*** Significant at 0.001

1.5.2.2 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 this case, I start with estimating the difference-in-difference estimate (β_2 in specification 1.1) using the observed data. The next step is to generate the placebo data for many times and run the model in specification 1.1 on this placebo data. I decided to create 10,000 placebo data sets. To create each placebo data, I randomly draw 204 Representatives[12] from all of the Representatives in this data and allow

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

each of them to randomly pick a month to adopt Twitter. I then run a model with specification 1.1 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.[13] The next step is to compare the actual difference-in-difference estimate in the first step with the distribution of the placebo estimates. I set the significance level at 0.05. To form a two-tailed test of level 0.05, I 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, I reject the hypothesis that it is equal to 0, otherwise I 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

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

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 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.

1.5.3 Representative-specific & Constituent-specific Effects

To elaborate more on the effect of Twitter adoption on Representatives' voting orientation and political misalignment, I introduced the Representative-specific and constituent-specific factors as moderators to this model in Specification 1.1. 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. I 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 111th 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.

1.6 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 inuences that affect their opinions, attitudes, and behaviors (Fang, Hu, Li, & Tsai, 2013; Iyengar, Van den Bult, & Valente, 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

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. I interacted each factor with twitter status in Specification 1.1.

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.

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 the 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

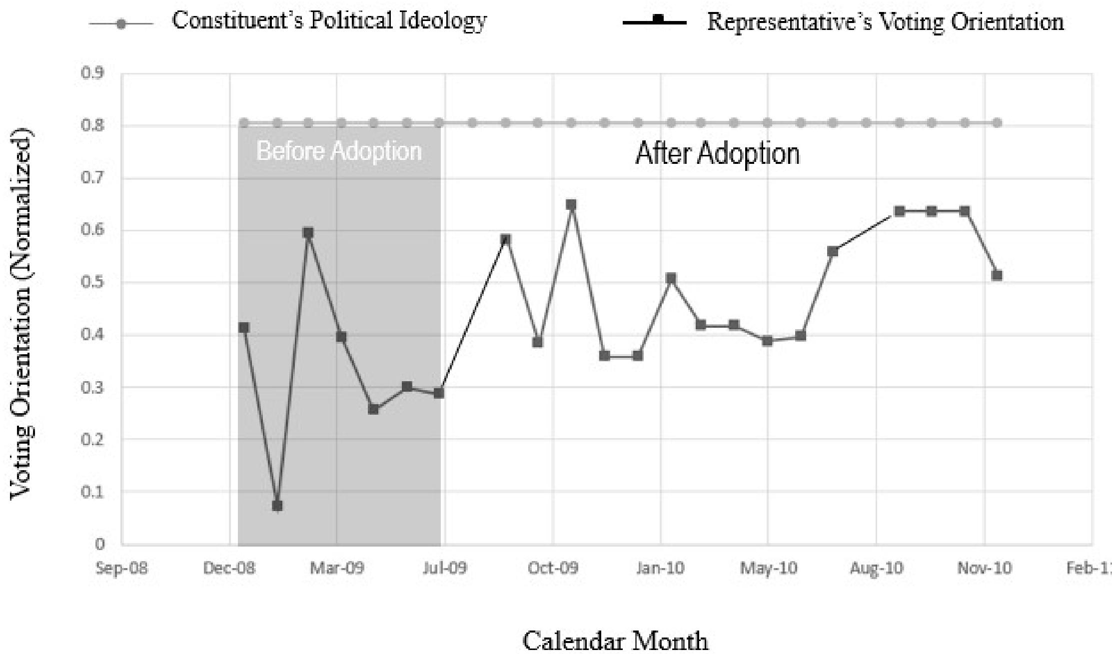

Figure 5. Changes in voting orientation of Representative Stephanie Sandlin (D-SD 1)

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.

In this study I 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

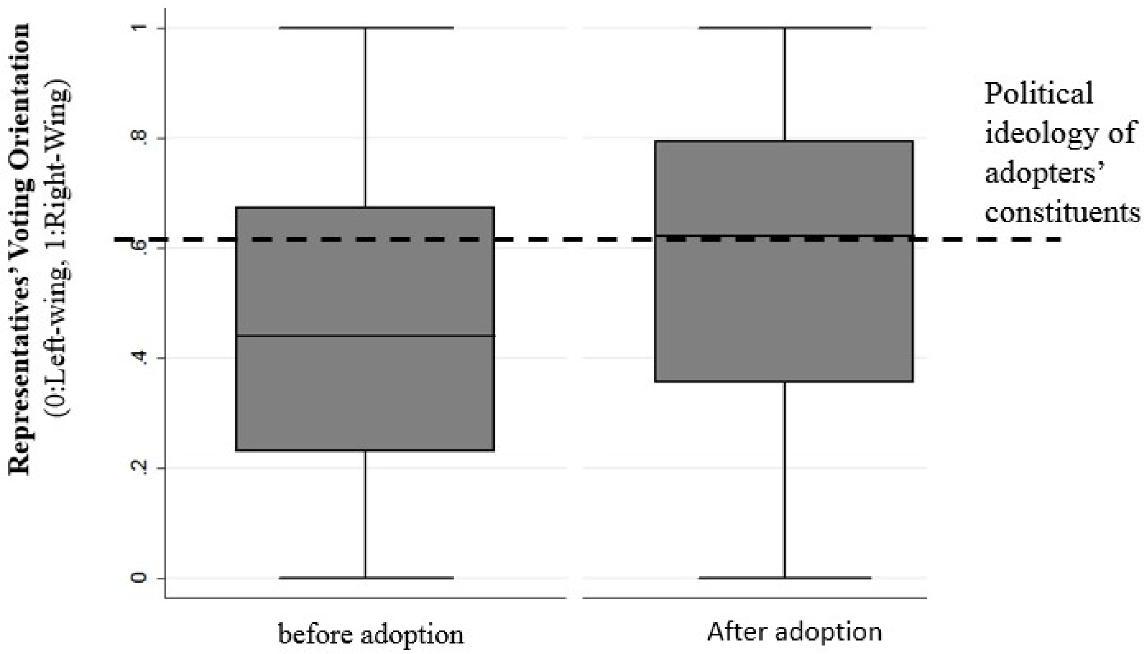

Figure 6. The Impact of Twitter Adoption on Voting orientation of Representatives Who Joined Twitter during The 111th Congress (The dashed line represents the political ideology of adopters' constituents).

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

It is worth mentioning that although I 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 the data set that shows a higher conservatism in Congressional districts during The 111th Congress.

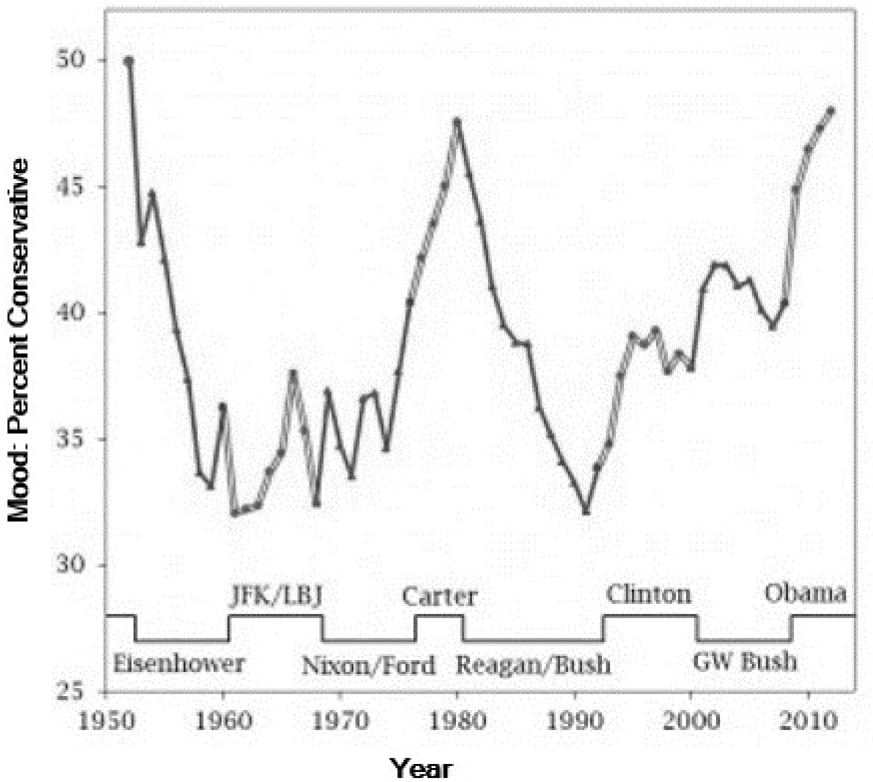

Figure 7. Americans' Conservative Policy Mood (Bartels, 2013)

1.7 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, I 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. I collected Representatives' data including their voting records, Twitter data, and the constituents' data. Using fixed effects and difference-in-difference approaches, the analysis revealed that the adoption of Twitter by directs them toward the conservative side of political spectrum. Furthermore, I 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 chapter and this shall be regarded as a limitation of this study, I 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.[14]

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. I 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, I created a

[14]In a separate study I 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. I 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, I 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.

Figure 8. A Tweet Addressed to John Carter (R- TX 31)

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. I observed a very high correlation between the two signaling a potential high accuracy for name-mention tweets.

Another limitation with regard to name-mention tweets and handle-mention tweets is that I don't know if these tweets were sent by the constituents. However, I argue that this information is not available to the Representatives for the most part. I 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 my 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 & 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, I 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.

Chapter 2

DOES TWITTER MAKE U.S. REPRESENTATIVES MORE POLARIZED?

Based on repeated expressions and peer influence literature, I examine the impact of elite politicians' online social networking behaviors on their partisanship behavior. I constructed a panel data for 414 Members of The 113th U.S. House of Representatives across a period of 9 months. To construct this panel, data from Twitter.com, The Library of Congress (THOMAS), The U.S. Census Bureau, voteview.com, and cookpolitical.com were collected. First, the findings suggest that repeated postings of party-preferred political tweets by Representatives increases the level of partisanship behavior by them. Second, following peers who frequently post party-preferred political tweets increases representatives' partisanship behavior. Third, the effect of following friends who frequently post party-preferred political tweets is larger than the effect of frequent postings of party-preferred tweets by Representatives themselves.

Keywords: Online Social Networking, Ideological Polarization, U.S. House of Representatives, Repeated Expressions, Peer Influence

2.1 Introduction

Online social network (OSN) platforms provide convenient conduits for individuals to express their opinions, interests, and viewpoints and interact with others. Politicians widely employ OSN platforms as an informal channel through which they express their opinions and standpoints. They also use these channels to hear the voices of peers and constituents in a convenient way. Numerous Washington Post, Time Magazine, NY Times, and Economist articles report about the extensive use of OSNs, especially Twitter, by politicians (Hicks, 2014; Parker, 2014; Rojas, 2013; Scherer, 2009). A study by Greenberg (2012) revealed that nearly 98% of the Representatives are active users of OSN platforms. Moreover, the analysis of the content generated by Representatives revealed that the majority of them are position-taking posts.

Although social media content has been studied for understanding the opinions of the general public and consumers regarding social events, political movements, company strategies, marketing campaigns, and product preferences (Bertot, Jaeger, & Grimes, 2010; Chen, Chiang, & Storey, 2012; Edvardsson, Tronvoll, & Gruber, 2011; Linders, 2012; Pang & Lee, 2008), little is known about the impact of OSN activities on politicians' decision making and their partisanship behavior. Given the abundant use of OSN platforms by politicians, and an ever increasing partisanship behavior observed in recent years in The U.S. House of Representatives, studying the potential effects of OSN activities on politicians seems urgent. Particularly, the two dominant perspectives about the influence of OSN platforms on partisanship behavior propose different predictions; in one perspective the proliferation of OSNs enables the users to be exposed to a broad range of opinions, attitudes, or even cultures and therefore develop a shared understanding with other users (Cairncross 1997; Friedman 2005). In the second perspective, velocity, volume, and variety of the content available on OSNs make users behave selectively in finding their OSN collaborators and narrow down their online interactions with like-minded users. Such effect in turn may create further partisanship behavior (McPherson, Smith-Lovin, & Cook, 2001; Sunstein, 2001, 2007a).

Therefore, I intend to study the impact of OSN activities of political elites on their voting behavior and the underlying theories behind this relationship. More specifically, I try to answer the following questions:

1. Do Representatives' OSN activities make them more ideological moderate or polarized?
2. How do OSN activities of Representatives' friends influence Representatives' ideological orientation?

This study could contribute to the IS research in three distinct ways:

First, this research evaluates two mechanisms of polarization; one based on repeated expressions literature (Binder, Dalrymple, Brossard, & Scheufele, 2009; M Brauer, Judd, & Gliner, 1995; Markus Brauer & Judd, 1996; Downing, Judd, & Brauer, 1992; Fazio & Williams, 1986; Powell & Fazio, 1984) and another based on peer influence literature (Axelrod, 1997; Godinho de Matos, Ferreira, & Krackhardt, 2014; Jackson & Dunia, 2012; Sunstein, 2001; Sykes, Venkatesh, & Gosain, 2009; Van Alstyne & Brynjolfsson, 2005; Y. Wang, Meister, & Gray, 2013). Although the latter has been studied in OSN context, the potential effect of repeated expressions in polarization yet to be studied.

Second, this unique dataset would enable us to compare the effects of the two mechanisms on ideological polarization. This would further shed light on the underlying relationships between use of OSNs and decision-making processes.

Third, the study deviates from previous studies since I evaluate the role of OSN use by elite politicians as subject matter experts rather than normal users. This would inform the understanding of changes in behaviors of elite experts due to their involvement with OSNs.

The organization of this chapter is as follows. In the next section, I review the theoretical background of ideological polarization and the influence of OSN on ideological polarization. In section 3, I present the data and variables. In section 4, I describe the empirical model. In Section 5, I present descriptive statistics along with the results of the analyses. In the subsequent sections, I discuss the findings and conclude with limitations and potential extensions of this study.

2.2 Theoretical Background

2.2.1 The Causes of Political Polarization

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

The political science research has rigorously addressed the major causes of political polarization in American policy making. Layman et al. (2006) studied the causes of party polarization in the U.S. Congress. Disagreements on critical issues and cultural and moral concerns, as Layman et al. (2006) maintained, are the major causes of party polarization in U.S. politics. Carmines & Stimson (1989) argued that during 60s and 70s civil right movements and the dramatic differences between Democrats and Republicans initiated the ever increasing American political polarization. The term "issue evolution" coined by Carmines & Stimson (1989) refers to the polarization as a result of differences between Democrats and Republicans with regard to a set of important issues. Other issues that triggered party polarization were related to cultural and moral concerns. Among them, one may include abortion, homosexual rights and school payers (Abramowitz & Saunders, 2008). In a sense, some of the researchers in this area believe that critical issues, cultural, and moral concerns trigger polarization in U.S. politics.

However, other researchers such as Cass R. Sunstein (2007a), Giovanni Sartori (2005), and Robert Axelrod (1997) argue that polarization could be an inevitable phenomenon when a set of society's attributes reach to certain points. This perspective believes that the structure of the society and the principle of homophily (the tendency of individuals to associate with others similar to themselves) majorly cause ideological polarization (Axelrod, 1997). One of the most influential studies in this domain was done by Axelrod (1997). He employed adaptive agent-based modeling to study the dissemination of culture and the ideological polarization in societies over time. Axelrod's model reveals how interactions of agents (individuals) could result in ideological polarization in the society. He suggests that agents' interactions tend to be more frequent and influential when the agents share a set of attributes with each other. As Rogers (1983) stated based on Homans' The Human Group seminal work, "The transfer of ideas occurs most frequently between individuals … who are similar in certain attributes such as beliefs, education, social status, and the like." (p. 278) In this perspective, the principle of homophily is one of the main drivers of ideological polarization. That is, like-minded individuals tend to interact with each other more frequently and more influentially. Therefore, they become even more similar over time and form groups. The similarity between the individuals within a group separates them from other groups. As Sunstein (2007a) suggested, group polarization increases when people have a shared sense of identity. Especially in cases that group members argue against another group, they tend to reveal more extreme opinions. In this sense, homophily contributes to polarization.

In a more holistic way, Sunstein (2007a) categorizes the causes of ideological polarization in three cohorts: the most important driver of polarization is related to informational influence. Sunstein argues that initial seeds of all groups are biased. This inclination attracts like-minded people to the group. As members listen to the discussions, they tend to lean more toward the initial inclination of the seed. Hence, extreme point of view is the result of the discussions of similar-minded group members over time. The second cohort is related to social comparison. I like to be liked. What I say is sometimes a function of what I want to be perceived from us by other people (particularly people who are important to us). If others value leaning toward an extreme opinion, group members may become more leaned toward that extreme to obtain more credit from others. The third cohort is related to confidence. "Agreements from others tend to increase confidence." (Sunstein, 2007a) More confidence in turn may make people more extreme.

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

2.2.2 Online Social Networks and Political Polarization

The proliferation of OSNs minimizes the cost of communication and enables the users to reach out other individuals with a variety of backgrounds. Therefore, OSN users could be exposed to a broad range of opinions, attitudes, or even cultures. This in turn may create a shared understanding among OSN users and discount their ideological differences (Cairncross, 1997; Friedman, 2005). On the other hand, velocity, volume, and variety of the content available on OSNs make users behave selectively in finding their OSN collaborators due to their bounded processing capacities. In other words, users tend to create filters through which they mostly receive signals aligned with their prior viewpoints (Sunstein 2001) and mostly interact with similar-minded folks (Gu et al., 2014; McPherson et al., 2001). Due to this, Flache & Macy (2006) argue that the emergence of homophily in OSNs is inevitable. Interaction with similar-minded people may in turn reinforce partisanship behaviors as opposed to nurturing the diversity of ideas (Axelrod, 1997; Sunstein, 2007a). As Van Alstyne and Brynjolfsson (2005) noted "[i]nternet users can seek out interactions with like-minded individuals who have similar values and, thus, become less likely to trust important decisions to people whose values differ from their own. This voluntary balkanization and the loss of shared experiences and values may be harmful to the structure of democratic societies as well as decentralized organizations." (p. 866)

Sunstein (2001) argues that internet technology enabled people to easily filter what they want to see, hear, or read. Nowadays, everyone is able to design her own newspaper, magazine, and TV channels. For instance, if someone is interested in a certain point of view in politics, she may restrict herself to hear only from people with the same perspective. "With the reduced importance of general interest in magazine and newspaper, and the flowering of individual programming design, different groups make fundamentally different choices." (Sunstein, 2001: p5) As Sunstein maintains, with the unlimited power of filtering, individuals can create their own communication universe. Customization features available in many online media further strengthens self-filtering phenomenon. Many websites can choose whatweare interested in just by knowing a little about us and our taste (Sunstein, 2007b). These websites then can suggest recommendations based on the tastes of like-minded people. This in turn may further promote the homophily within the group of similar-minded individuals and subsequently elevate ideological polarization. It is worth noting that the impact of homophily, and the subsequent peer influence, on network users has been extensively researched in IS and other disciplines. A substantial number of these studies examined the impact of peer influence on technology use, online product ratings, and decision making (El-Shinnawy and Vinze 1998; Godinho de Matos et al. 2014; Sykes et al. 2009; Wang et al. 2013; Wattal et al. 2010). Others studied the role of peer influence in dissemination of ideas and cultures (Jackson & Dunia, 2012), and stock market participation (Brown, Ivkovic, Smith, & Weisbenner, 2008). This perspective hinges around the influence of peers on group members' decisions. However, not only OSNs facilitate the communications among peers, but also they provide conduits for individuals to repeatedly express their opinions. According to Powell & Fazio (1984), repeated attitude expressions increase the accessibility of the attitude. Increases in accessibility in turn lead to greater attitude–behavior consistency (Fazio & Williams, 1986). Drawing from Fazio's studies, Downing et al. (1992) proposed that repeated expressions are at least partly responsible for attitude extremity. This proposition was further studied and supported by Brauer et al. (1995). Particularly, another study by Binder et al. (2009) based on data from a nationwide mail panel survey carried out between 2002 and 2005 revealed that political talk plays a substantial role in shaping and polarizing attitudes on a given issue; discussions in networks composed of like-minded others directly lead to the development of extreme attitudes. As Brauer & Judd (1996) concluded, the social psychology literature suggests that "individuals polarize in group discussions in part because they frequently express their own opinions and arguments as well as listen to the arguments and opinions of other group members." (p. 203) According to this statement, there are two effects that could contribute to polarization: 1- repeated expressions of own opinions, and 2- listening to the arguments of other group members (peer influence). If we suppose that the Democrats shape one group and the Republicans shape another group, within-group political discussions could result in political polarization. Therefore, I hypothesize that:

H1: Repeated expressions of party-preferred political opinions through twitter increase ideological polarization of the Representatives.

H2: Following peers who post party-preferred political tweets on Twitter increases ideological polarization of the Representatives.

2.3 Data & Variables

2.3.1 Twitter Data

Using scripts in Python programming language, I collected data from Twitter API since September 21st, 2013 to May 31st, 2014. The data set contains 184,476 tweets posted by Members of the 113th House of Representatives. From this dataset, I excluded the tweets posted before the time span of this study. This resulted in 154,534 tweets posted by Representatives during the calendar months August 2013 to May 2014. Moreover, I collected the list of followers and followings for each Representative at the end of each month during the time span of the study.

Since the content of the tweets vary, they may not have the same impact on political polarization of the Representatives. For instance, some of the tweets may be quite personal while others may reveal important opinions of the Representative. Moreover, some of the tweets are in line with the political orientation of Representative's party while some other might be against the proposed position of the party. To extract politically relevant tweets posted by Representatives, the literature suggests a coding procedure (Greenberg, 2012). In this procedure, each tweet will be coded based on sentiment, reference to the party, and purpose. Based on purpose, a tweet can be classified into the following categories: 1- campaign-related tweets, 2- tweets about official congressional actions, 3- position taking tweets, 4- policy statement tweets 5- district or state related tweets 6- media or public relations tweets, 7- personal tweets, and 8- others. Table 12 represents a snapshot of the output of the coding procedure. According to table 12, Representative Kevin Brady tweeted a negative opinion about the opposing party. In contrast, Representative George Miller posted a positive tweet in favor of his own party. Since both of these tweets are admired by the Representative's own party, I call these tweets party-preferred tweets. Therefore a party-preferred tweet is a tweet with a positive sentiment about Representative's allied party, or a negative tweet about Representative's opposing party.

Given the size of the data set, manual coding of the tweets could be challenging. Therefore, I employed text mining techniques to detect party-preferred tweets posted by Representatives. To do so, I initially set up three training data sets for each classification task. I hired two independent coders who read and classified 7,727 tweets

Table 12. Snapshot of the Output of the Proposed Coding Procedure

Representative	Tweet	Sentiment		Reference		Purpose
Kevin Brady (R-TX 8th District)	The cancellations lay bare 3 pillars of #Obamacare: (a) mendacity, (b) paternalism and (c) subterfuge.	Negative	-1	Opposing party	-1	Position taking
George Miller (D-CA 11th District)	I'm proud to stand with my fellow Democrats who know it's #timefor1010 and time to #RaiseTheWage	Positive	+1	Allied party	+1	Policy Statement

(5% of all of the tweets) based on purpose, sentiment, and reference. It is worth noting that each coder was provided with the same manual consisting of the guidelines for coding the tweets as well as numerous examples of manually coded tweets by the authors. Cohen's Kappa for sentiment, reference, and purpose categorizations were 0.841, 0.813, and 0.802 respectively, signaling an almost perfect agreement between coders (Hallgren, 2012). In case of disagreements, a third coder made the final decision. As mentioned earlier, there were 8 different categories for purpose. Not all of these categories have the same political weight. Therefore, I had to remove the tweets that are not positioned politically. For instance, campaign-related tweets, media or public relations tweets, and personal tweets don't have the same political weight that position taking and policy statement tweets yield. For this reason, I created two groups of tweets based on purpose: 1- Relevant tweets: all of the tweets categorized in official congressional actions, position taking, and policy statement fall into this group. 2- Irrelevant tweets: all of the tweets categorized in campaign-related, district or state related, media or public relations, personal, and others fall into this group. To construct the regressors in the econometric model, I only used relevant tweets. To identify the relevant tweets, I trained the machine learning classifier to separate relevant and irrelevant tweets. I used 3,779 manually coded irrelevant tweets and 3,948 manually coded relevant tweets to train a Support Vector Machine (SVM) classifier in RapidMiner version 5 (Jungermann, 2009). I employed polynomial kernel type set at

2.0 kernel degree and 200 cache. The convergence epsilon was set at 0.001 and the maximum iterations was set at 100,000. To create the word vectors, I used TF-IDF with percentual prune method. Prune below was set at 1% and prune above was set at 98%. Table 13 reports the accuracy of this classifier measured by cross-validation method with 10 folds. The overall accuracy is the percentage of total tweets classified correctly (as relevant or irrelevant). Class-level recall is the percentage of tweets associated with a particular class that were classified as such. For example, relevant recall is the percentage of all relevant tweets in the test bed that are classified as relevant. Figure 2 illustrates the training process performed in RapidMiner to train the classifiers. Using this classifier, I separated 100,005 irrelevant tweets from 54,529 relevant tweets.

Table 13. Purpose Analysis Accuracy

Accuracy: 81.23%			
	True Irrelevant	True Relevant	Class Precision
Pred. Irrelevant	2933	760	79.42%
Pred. Relevant	654	3188	82.98%
Class Recall	81.77%	80.75%	

The next step is to identify the sentiment and the reference of the relevant tweets. To identify the sentiment of each tweet, I set up a training data set from the repository of manually coded tweets. I created a negative class consisting of 1,920 negative tweets, and a positive class including 994 positive tweets. I adopted the same algorithm that I used to detect relevant tweets to train and classify the tweets based on their sentiment. Only this time I used SVM with dot kernel type with 200 kernel cache. The convergence epsilon was again set at 0.001 and the maximum iterations was set at 100,000. To create the word vectors, I used TF-IDF with percentual prune method. Prune below was set at 3% and prune above was set at 95%. This resulted in identifying 39,935 negative tweets and 14,594 positive tweets. Table 14 reports the accuracy of this classifier. It is worth mentioning that this accuracy is higher than the average accuracy reported for Twitter sentiment analysis performed by RapidMiner (Abbasi, Hassan, & Dhar, 2014). There could be two reasons for this higher accuracy: 1- Before performing sentiment analysis, I removed the irrelevant tweets from the data set. The remainder are tweets about position taking, policy making, and official congressional actions. This process resembles Pang and Lee's (2004) approach and would result in a more refined Twitter data set for sentiment and reference analysis. 2- All of the tweets in the data set are posted by politicians who are subject matter experts and may use similar terminologies in their posts.

Table 14. Sentiment Analysis Accuracy

Accuracy: 81.52%			
	True Neg.	True Pos.	Class Precision
Pred. Neg.	1476	148	90.89%
Pred. Pos.	444	1136	71.90%
Class Recall	76.88%	88.47%	

To identify the reference of each tweet with regard to the political party, I set up

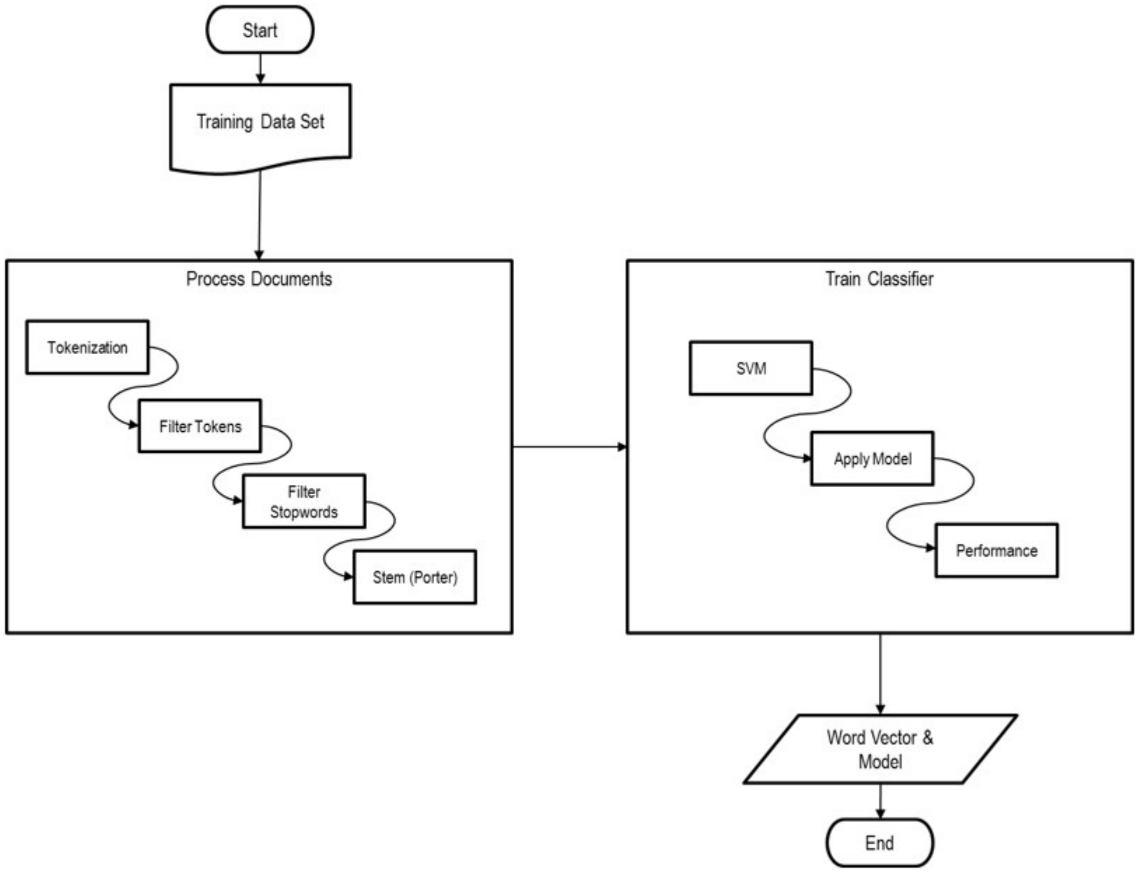

Figure 9. Classifier Training Process

another training data set from the repository of manually coded tweets. I created a Democrats class consisting of 1,240 tweets that referred to the Democrats political party, and a Republicans class including 1,289 tweets referring to the Republican political party. I adopted the same algorithm that I used in purpose analysis to train and classify the tweets based on their reference. Table 15 reports the accuracy of this classifier. Although I also attempted hashtag co-occurrence approach as described in (Conover et al., 2011) to detect the political reference of the tweets, the accuracy achieved by the classifier was higher. Figure 3 summarized the text mining approach to extract the relevance, sentiment, and reference of each tweet.

Table 15. Reference Analysis Accuracy

Accuracy: 80.55%			
	True Dem.	True Rep.	Class Precision
Pred. Dem.	967	219	81.53%
Pred. Rep.	273	1070	79.67%
Class Recall	77.98%	83.01%	

After identifying the reference of the tweet with regard to the political party, I had to identify whether the tweet is referring to the Representative's allied party or the opposing party. To do so, I compared the political party of the Representative who posted the tweet with the reference of the tweet using a script in Python. I created a dummy variable that takes the value of zero if the tweet is about the opposing party, and 1 if the tweet refers to the allied party. It is worth noting that the joint accuracy of detecting party-preferred tweets was 73.29

The last step is to construct the variable called Preferred_Tweets. This variable was constructed by summing the number of positive tweets with reference to the allied party and negative tweets with reference to the opposing party for each month. For instance, if Representative i posts 2 negative tweets about the opposing party and 4 positive tweets about his own party during time period t, the value of Preferred_Tweets variable for him for time period t will be 6.

To be able to test the second hypothesis, I needed to construct another variable that captures the effect of connecting to friends who post Preferred_Tweets. Each Twitter user is fed only by the tweets posted by users she follows on Twitter or sponsored

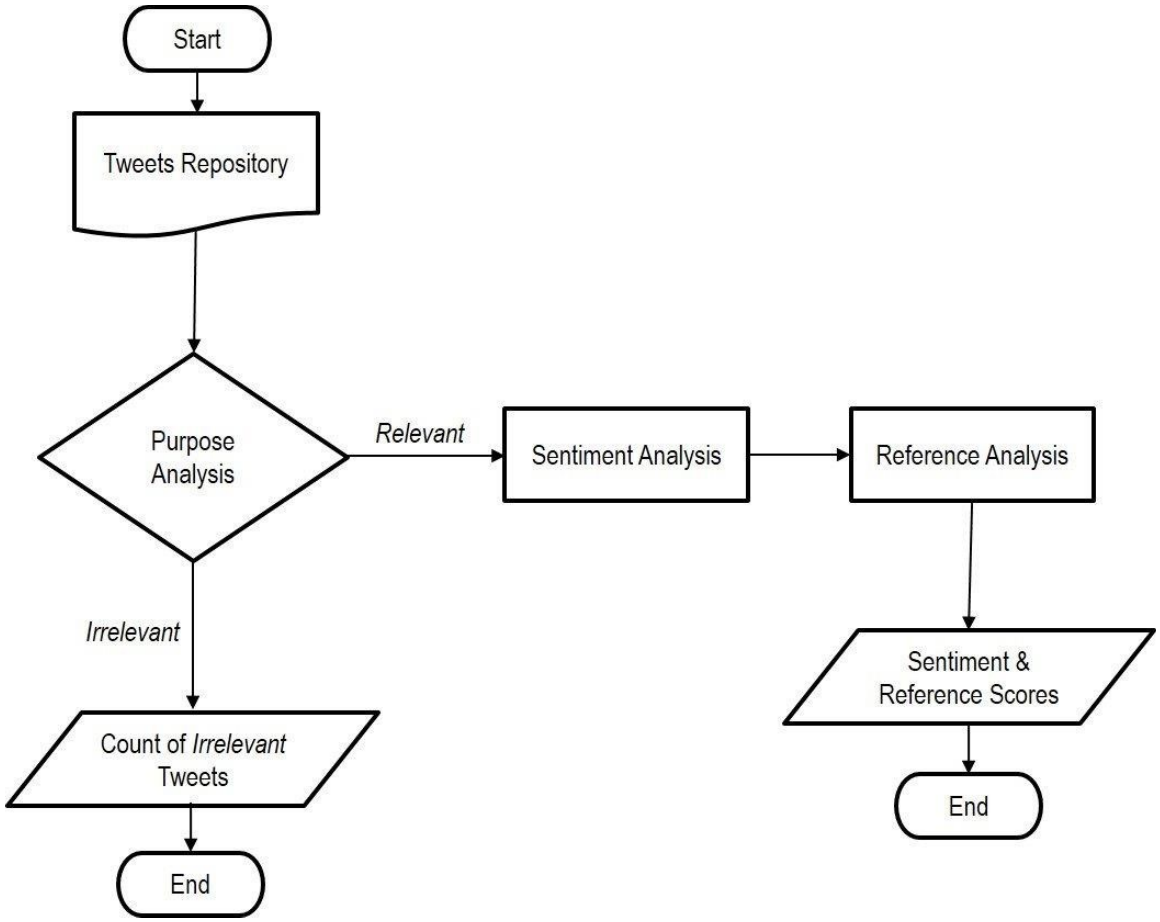

Figure 10. Text Mining Process

tweets by advertisers. Therefore, it seems to be fair to assume that Representatives are impacted, if any, only by tweeting activities of people they follow on Twitter. Based on the data though, Representatives follow an average of 4,123 users on Twitter and it seems impossible for a Representative to read all of the tweets posted by his Twitter friends. Therefore, I narrow down the friends list to those friends who are also serving in The Congress. To construct the variable Friends_Effect I calculated the arithmetic mean of Preferred_Tweets posted by Representative's friends during each month. A high value for this variable means that the Representative follows peers who share Preferred_Tweets more frequently. In contrast, the value of this variable would be small if Representative's friends are not posting Preferred_Tweets. This approach would make Friends_Effect comparable to Preferred_Tweets.

2.3.2 Polarization Data

For each month of the study, I estimated the measure of Representatives' ideological polarization based on votes cast by each Representative in a given month. I used the first dimension of Weighted Nominal Three-Step Estimation (WNOMINATE), a widely used estimation model in political science, for the estimation (Poole, Lewis, Lo, & Carroll, 2011). WNOMINATE is "a scaling procedure that performs parametric unfolding of binary choice data." (Poole & Rosenthal, 1985) Given a matrix of binary choices by individuals (for example, Yea or Nay) over a series of Parliamentary votes, WNOMINATE produces a configuration of legislators and outcome points for the Yea and Nay alternatives for each roll call using a probabilistic model of choice. WNOMINATE creates a spectrum of scores ranging from -1 to +1, with -1 representing the most Liberal Representative and +1 representing the most Conservative Representative. The WNOMINATE scores have been employed by numerous social scientists to study the behaviors of the politicians, mainly ideological polarization, based on their voting records (Aldrich & Battista, 2002; Aldrich, Montgomery, & Sparks, 2014; Lupu, 2013). Since we are interested in the magnitude of the political polarization rather than its direction, I employed the absolute value of the WNOMINATE scores as a measure of polarization. This variable ranges from 0 to 1, with 1 being the highest level of ideological polarization (either extreme Democrat or extreme Republican) and 0 being the lowest level of ideological polarization.

2.3.3 Constituent's Data

I adopted Cook's partisan voting index (PVI) developed and introduced by Charlie Cook in 1997 as a measure of constituents' political orientation. Cook's PVI is a measurement of how strongly a United States congressional district leans toward the Democratic or Republican Party, compared to the nation as a whole. Cook employs the last two presidential election results as a baseline for gauging the political orientation of each congressional district (Cook & David, 2014; Nunnari, 2011). I obtained Cook's PVI for each congressional district during 113th Congress. Cook's PVI for the 113th Congress ranges from 0 to 29 for Republican districts and from 0 to 41 for Democrat districts. During the 113th Congress, New York's 14th and 15th districts with a PVI score of D+41 were the most liberal districts while Texas's 11th and 13th districts with a PVI of R+29 were the most conservative districts. I rescaled Cook's PVI to match the WNOMINATE measures. In the dataset Cook's PVI ranges from -1 to +1 with -1 being the score for the most liberal congressional district and +1 being the score for the most conservative district. Again, since we are interested in the magnitude of the political polarization rather than its direction, I employed the absolute value of the scaled PVI scores as a measure of constituents' political polarization. This variable ranges from 0 to 1, with 1 being the highest level of polarization (either extreme Democrat or extreme Republican district) and 0 being the lowest level of polarization.

I also collected data from The United States Census Bureau for constituents' internet access and voteview.com for Representatives' party affiliation. Table 16 reports all of the sources of data for this study.

2.4 Empirical Model

I employed a two-step empirical model:

1. Fixed effects specification to estimate the coefficients for Preferred_Tweets and Friends_Effect. With panel data, the FE estimation procedure gives the consistent estimates of the parameters on time-varying variables. However, the estimation cannot identify the effects of the time-invariant variables, such as the effect of constituent's political polarization and party affiliation due to the fact that all of the time-invariant variables in the model are removed in the FE estimation procedure. Under this specification, I propose the model of Representatives' ideological polarization as:

$$y_{it} = \beta_0 + \beta_1 x_{1it-1} + \beta_2 x_{2it-1} + \beta_3 x_{3it-1} + T_t + \alpha_i + \epsilon_{it} \tag{2.1}$$

Where i is the index for Representatives and t is the index for time, t = 09-2013, 10-2013, ... , 05-2014; $y_i t$ is Representative i's ideological polarization at time t, x_{1it-1} is the count of party-preferred tweets (Preferred_Tweets) posted by Representative i at time t-1, x_{2it-1} is the mean of party-preferred tweets posted at time t-1 by Representative i's Twitter friends who serve in the Congress, x_{3it-1} is the number of bills Representative i cosponsored with his/ her Twitter friends at time t-1, T is a vector of time-fixed effects, α_i is the fixed effects for Representative i, and ϵ_{it} is the error term. I adopted from (Clemens, Radelet, Bhavnani, & Bazzi, 2012) and employed 1 month lagged Preferred_Tweets and Friends_Effect to avoid potential simultaneous causation. Another issue to be addressed in this model is the effects of offline interactions among the Representatives. Aside from the online interactions, the Representatives may have significant offline exchanges with their colleagues. Therefore, one could argue that the offline interactions among the Representatives are the actual drivers of the changes in the ideological polarization and the online transactions are mere reflection of those offline transactions. To account for the potential effects of the offline transactions, I counted the number of times each Representative cosponsored a bill with his/ her Twitter friends during each month of the study. The logic is that Representatives who have higher offline interactions with each other would cosponsor more bills together. The cosponsorship network has been rigorously studied in the political science (Fowler, 2006a, 2006b) and has been tied to the political polarization of the Representatives (Zhang et al., 2008).

2. Zero- One Inflated Beta Regression (ZOIB) estimation. The reason for using this specification is that the values of the political polarization is bounded to range from zero to one. Since the OLS specification assumes a normal distribution, the linear specification may not work in this setting. According to (Kieschnick & McCullough, 2003), parametric regression models based on beta distribution are recommended for these data. Particularly, the ZOIB model has been previously used in political science literature when WNOMINATE scores were employed to construct the outcome variable (Burmester & 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, 2010). It is worth noting that ZOIB specification would also allow us to introduce time-invariant repressors such as Representatives' demographic data and factors related to their constituents.

2.5 Results

Table 16 represents the descriptions, sources of the data, and summary statistics. According to table 16, the mean of ideological polarization of the Representatives is almost in the middle of the spectrum. However, comparing this measure with the mean of constituents' political polarization reveals that Representatives, on average, are more polarized than the constituents. Table 16 also reveals that Representatives post usually more than 5 Preferred_Tweets during each month. However, their friends usually post one more party-preferred tweet each month.

The number of Republican Representatives in this sample (all of the Representatives who had Twitter account during the period of this study) is slightly higher than the count of Democrats, which is almost identical to the body of The 113th Congress as there are 233 Republican Members and 199 Democrat Members. As discussed earlier, constituents are less polarized than their representatives. Last but not least, more than 76% of the constituents, on average, have access to the internet according to the data from U.S. Census Bureau released in 2012.

Table 17 reports the results of the FE and ZOIB models, which are based on Equation (1). For the ZOIB models, I also reported the marginal effects to be able to compare the magnitude of the effects. According to table 17, Preferred_Tweets and Friends_Effect are both positive and significant in all models. The control for the offline interactions, Cosponsor_Friends, is significant and negative in the FE model but not significant in the ZOIB model. Furthermore, the impact of Friends_Effect on Representative_Polarization is higher than the impact of Preferred_Tweets posted by Representatives themselves. Moreover, according to model 4 Party_Affiliation, Constituent_Political_Polarization, and Constituent_Internet_Access are not significant.

Table 16. Variables, Descriptions, & Summary Statistics

Variable	Description	Source of Data	Mean	Std. Dev.	Min	Max
Representative_Polarization	Representative's ideological polarization (time varying)	The Library of Congress (THOMAS) & voteview.com	0.486	0.271	0	1
Preferred_Tweets	Count of party-preferred tweets posted by Representative (time varying)	Twitter API	5.458	8.306	0	190
Friends_Effect	Mean of count of party-preferred tweets posted by Representative's Twitter friends who are also Representatives (time varying)	Twitter API	6.557	3.629	0	35.333
Cosponsor_Friends	Number of bills cosponsored by Twitter friends during each month (time varying))	Sunlight Foundation API	5.587	4.001	0	29
Party_Affiliation	Representative's political party (time-invariant; equals 1 if Republican and 0 otherwise)	voteview.com	0.539	0.499	0	1
Constituent_Political_Polarization	Rescaled absolute value of Cook's PVI (time-invariant)	cookpolitical.com	0.333	0.231	0	1
Constituent_Internet_Access (%)	Percentage of the constituent who have internet access (time-invariant)	U. S. Census Bureau	76.390	4.839	61.400	87.100

To test for heteroskedasticity I exploited modified Wald test for group-wise heteroskedasticity in fixed effects regression model. Since I identified the presence of heteroskedasticity, I employed Eicker-Huber-White robust standard errors in all models. To decide between random and fixed effect models, I employed Hausman test. The RE estimation procedure can estimate the parameters of all the time-varying and time-invariant variables in the model under the assumption that all the independent variables are independent of the fixed effects. Hence, I test for the assumption to decide whether the RE estimation is appropriate for the model. The result was in favor of the fixed effect model ($p<0.001$). I also tested for the time-fixed effects by a joint test to see if the dummies for all months are equal to zero. I identified the presence of time-fixed effects. Therefore I generated time dummies to obtain the two level fixed effects estimators in all FE models and incorporated time dummy variables in ZOIB models to control for omitted variables that vary over time but are constant across the units.

Table 17. FE and ZOIB Estimation Results (DV = Representative_Polarization)

Variable	Model 1	Model 2	Model 3		Model 4	
			Coefficients	Marginal Effects	Coefficients	Marginal Effects
Preferred_Tweets (lagged)	**0.001*** **(<0.001)**	**0.001*** **(<0.001)**	**0.006*** **(0.003)**	**0.001*** **(<0.001)**	**0.006*** **(0.003)**	**0.001*** **(<0.001)**
Friends_Effect (lagged)	**0.015***** **(0.003)**	**0.016***** **(0.003)**	**0.054***** **(0.014)**	**0.012***** **(0.003)**	**0.058***** **(0.014)**	**0.013***** **(0.003)**
Cosponsor_Friends		**-0.004*** **(0.002)**			-0.017 (0.009)	-0.004 (0.002)
Party_Affiliation					-0.016 (0.025)	-0.004 (0.006)
Constituent_Political_Polarization					2.503 (2.749)	0.565 (0.621)
Constituent_Internet_Access (%)					-0.067 (0.066)	-0.015 (0.015)
Time-fixed effects	√	√	√		√	
Representative-fixed effects	√	√	√		√	
Robust	√	√	√		√	
Clustered	√	√				
F (Wald χ^2 in ZOIB) p-value	74.59 $p<0.001$	65.61 $p<0.001$	1372.36 $p<0.001$		1339.57 $p<0.001$	
Specification	FE	FE	ZOIB		ZOIB	
R-squared (within)	0.215	0.221	-		-	

I also tested for cross-sectional dependence using Breusch-Pagan LM test of independence and Pesaran cross-sectional dependence. Pesaran cross-sectional dependence test is used to test whether the residuals are correlated across subjects. Cross-sectional dependence can lead to bias in tests results (also called contemporaneous correlation). The results of the tests did not signal the presence of cross-sectional dependence. I further employed Wooldridge test for autocorrelation in panel data; which signaled the presence of serial correlation. Therefore I used clustered errors at the panel level in models 1 and 2. If there is serial correlation in the idiosyncratic error term, clustering at the panel level will produce consistent estimates of the standard errors as discussed in (Wooldridge 2002: p177).

2.6 Discussion

The goal was to study the potential impacts of two distinct mechanisms on ideological polarization of an elite population. The first mechanism, is the effect of Representatives' own tweeting habits. The second mechanism taps the influence of Representatives' social media friends.

2.6.1 Representative's Own Tweeting Habits

According to the findings in table 17, repeated expressions of party-preferred opinions in Twitter contribute to ideological polarization. This finding is still valid if I control for the effects of party affiliation and constituent's characteristics. This finding is consistent with the social psychology literature that has tapped the influence of repeated expressions on attitude polarization in a variety of contexts. Powell & Fazio

(1984) argue that repeated attitude expressions increase the accessibility of the attitude. Increases in accessibility of the attitude in turn lead to greater attitude–behavior consistency (Fazio & Williams, 1986). According to this domain of research it would make sense that the more a user tweets in favor of a position, the more vehemently that person will maintain his or her position. Particularly a study by Binder et al. (2009), based on data from a nationwide mail panel survey carried out between 2002 and 2005, revealed that political talk plays a substantial role in shaping and polarizing attitudes on a given issue; discussions in networks composed of like-minded others directly lead to the development of extreme attitudes. As Brauer & Judd (1996) concluded, the social psychology literature suggests that "individuals polarize in group discussions in part because they frequently express their own opinions and arguments as well as listen to the arguments and opinions of other group members." This finding about the first hypothesis suggests that Representatives who frequently post tweets that are favorable by their allied party, tend to become more extreme over time.

2.6.2 Friends' Effect

The second important mechanism I studied is the effects of social media friends. According to Sunstein (2007a), there are several mechanisms that could drive ideological polarization. Informational influence however, as Sunstein argues, is the most significant driver of ideological polarization. This cohort suggests that individuals become more convinced of their views when they hear novel arguments in support of their position (Vinokur & Burstein, 1974). As group members listen to the discussions, they tend to lean more toward the initial inclination that was the basis for group foundation. Hence, extreme point of view is the result of the discussions of similar-minded group members over time.

To evaluate the presence of homophily in Representatives' Twitter network, I created the network of Representatives' connections based on Twitter following/ follower relationships. Not surprisingly, the inter-group (party) edges in this network are denser than the intra-group edges in this graph. Nearly 87% of the edges of this network were among Representatives from the same party. Givan-Newman modularity of this graph was 0.336 and the graph density is 0.216. Overall, the following/ follower network of the Representatives indicates that a great level of homophily exists in Representatives' Twitter relationships.

Sunstein (2001) argues that internet technology enabled people to easily filter what they want to see, hear, or read. Nowadays, everyone is able to design her own newspaper, magazine, and TV channels. For instance, if someone is interested in a certain point of view in politics, she may restrict herself to hear only from people with the same perspective. "With the reduced importance of general interest in magazine and newspaper, and the flowering of individual programming design, different groups make fundamentally different choices." (Sunstein, 2001: p5) As Sunstein maintains, with the unlimited power of filtering, individuals can create their own communication universe. There is no surprise that Representatives, as elite politicians, create such universe for themselves. Customization features available in many online media further strengthens self-filtering phenomenon. Many websites can choose what we are interested in just by knowing a little about us and our taste (Sunstein, 2007b). These websites then can suggest recommendations based on the tastes of like-minded people. This in turn may further promote the homophily within the group of similar-minded individuals and subsequently elevate ideological polarization.

These findings in table 17 suggest that Friends_Effect is significant and positive in all models, confirming the second hypothesis. A comparison between the coefficients of Representative's party-preferred tweets and Friends_Effect reveals that the influence of friends on ideological polarization is larger than the effect of Representative's own tweeting habits. This finding sheds more light on the mechanisms of ideological polarization. Friends_Effect on Representative_Polarization is still significant and positive even when I control for the offline interactions among the Representatives by introducing the number of bills they cosponsored with their Twitter friends.

2.7 Conclusion

By collecting all of the tweets posted by 414 Members of The 113th House of Representatives, their voting records, party affiliation, and constituent's data over a 9-month period I studied the impact of OSN activities on Representatives' ideological polarization. The body of knowledge suggests that there are at least two mechanisms that contribute to the ideological polarization. The first mechanism relates to the repeated expressions of opinions. Repeated expressions of attitudes escalate the accessibility of the attitude. Increases in accessibility of the attitude, subsequently, lead to greater attitude–behavior consistency (Fazio & Williams, 1986). These findings suggest that this mechanism is functional in Twitter platform for elite politicians. That is, Representatives who frequently tweet party favorable content would eventually vote more consistent with their allied party. The second mechanism relates to the effect of peer influence. Political discussions in networks composed of like-minded others directly lead to the development of extreme attitudes, thus ideological polarization. Another interesting finding of this study is that peer influence has a higher impact on ideological polarization than do Representatives' own tweeting habits. Furthermore, the analyses are based on behaviors and decisions of elite politicians who are subject-matter experts. This deviates from prior studies in which ordinary users have been studied.

2.8 Limitations & Future Research

One of the limitations 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 shall be limited to the elite politician population. To better extend the realm of this research, one may study the dynamic network of politicians in social media. Such network can be built based on conversations in online social networking platforms. The Twitter platform enables users to mention another user or to retweet another user's tweet. Therefore, dynamics networks could be created based on the mentions and retweets among the users. A dynamic network analysis may shed more light on the underlying mechanism that causes the change in political orientation. Moreover, I 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 social media platforms by politicians on their political polarization. Although Twitter is sometimes perceived as a broadcasting medium rather than a social network, it shares certain features with other online social networking platforms. For instance, Twitter enables the users to follow and be followed by others. Twitter also recommends out of network users based on the current network of followers/ followings. However, replicating this study in other online social networking platforms with different set of features may enable the researchers to examine information-richness of the networks and thus elaborate on the mechanism of influence on greater detail.

Another interesting avenue for extending this research is to incorporate the OSN activities of Representatives' constituents. After all, Representatives are elected to represent the opinions of their constituents. Therefore, it would be interesting to study the impact of constituent-generated content on ideological polarization of the constituents. Furthermore, I suggest future researchers to evaluate the impact of constituents' social media posts and political polarization on the tweeting habits of their representatives.

Chapter 3

THE EFFECTS OF HOMOPHILY IN TWITTER COMMUNICATION NETWORK OF U.S. HOUSE REPRESENTATIVES: A DYNAMIC NETWORK STUDY

By employing a recently developed dynamic network model (separable temporal exponential-family random graph model), I study the effects of homophily based on gender, race, and political party on formation and dissolution of Representatives' Twitter communications in forms of mentions and retweets over a period of six month. The results indicate the presence of demographic homophily and value homophily in Representatives' Twitter communications networks. More importantly, I find that female Representatives and Representatives from minor ethnical groups have a high tendency in forming and persisting Twitter communications with similar Representatives. I also observe that homophily based on demographics such as gender and race is more effective in Mentions network while homophily based on political party is more dominant in Retweets network.

Keywords: Online Social Networking, Twitter, Dynamic Networks, Homophily, Exponential-family Random Graph Model (ERGM), Separable Temporal ERGM.

3.1 Introduction

Homophily (the tendency of individuals to associate with others similar to themselves) has been reportedly identified as one of the main drivers of network formation (Gu, Konana, Raghunathan, & Chen, 2014; McPherson, Smith-Lovin, & Cook, 2001). The majority of the previous studies treated social networks as static networks where the ties between the nodes are assumed to be constant and permanent. That is, the relationships among the nodes are not allowed to change over time. However in certain contexts such as in case of communications among social media users, the relationships may form and dissolve over time. Furthermore even in studies where the ties are allowed to change over time (dynamic networks), the underlying change mechanism in the network is only allowed to be the tie formation mechanism rather than both tie formation and tie dissolution mechanisms. Since social media users may have different reasons for forming a tie rather than breaking an existing tie, theoretically speaking it would be informative to allow both tie formation and tie dissolution in dynamic networks (Krivitsky & Handcock, 2014). Such a setup would allow the researcher to study the underlying mechanisms of the changes in dynamic networks by considering both formation and dissolution of ties.

Therefore, I employed recently developed Separable Temporal Exponential-family Random Graph Model (STERGM) to study the effects of homophily based on party affiliation, gender, and race on tie formation and dissolution of U.S. House Representatives' online communications on Twitter. STERGM, introduced by Krivitsky and Handcock (2014), is an extension of Exponential-family Random Graph Model (ERGM) for modeling dynamic networks in discrete time. The cross-sectional ERGM entails a single network, and a single model on that network. STERGM, in contrast, posits two models: one ERGM underlying tie formation, and a second one underlying tie dissolution. This approach is not simply a methodological development, but a theoretical one as well. Particularly in cases where the statistical model underlying tie formation can be different from the statistical model underlying tie dissolution (e.g. gender homophily may turn out to be a significant driver of tie formation, but not significant in tie dissolution) this approach would provide a proper framework for studying the phenomena. Therefore, I argue that STERGM model creates a unique setting where various effects of homophily on both tie formation and tie dissolution can be studied. This approach deviates from previous studies where either the network was treated as static (Conover et al., 2011; Susarla, Oh, & Tan, 2011; Yardi & Boyd, 2010; Zeng & Wei, 2013), or even in case of dynamic network studies, only the tie formation was studied and tie dissolution was either not relevant (Aral, Muchnika, & Sundararajan, 2009; Bampo, Ewing, Mather, Stewart, & Wallace, 2008) or simply ignored (Tarbush & Teytelboym, 2012). In this study, I intend to respond to McPherson et al. (2001) call for research by studying the "dynamics of network change over time through which networks and other social entities co-evolve."

In the followings, I start with briefly reviewing the theoretical foundation of homophily with respect to gender, race, and political party affiliation. Next, I review the literature of ERGM and STERGM. Then, I describe the data and present the empirical model for studying the role of homophily in tie formation and dissolution in Twitter communication networks of U.S. House Representatives. Next, I present the results. Finally, I discuss the findings and conclude with the implications.

3.2 Theoretical Background

There are two major reasons for why homophily exists in social networks. First, people are social entities who like to be liked. Since similarity could be a reason for social bonding and belongingness feeling, more interactions with similar others may increase the chance of being liked (Lakin & Chartrand, 2003). Second, people like to feel confident by getting approvals and endorsements from others. Since it is more likely for people to get approvals from similar others, increasing the interactions with similar others may increase approvals from them, thus increase confidence (Festinger, 1954).

According to McPherson et al. (2001), homophily can be based on demographic characteristics (such as gender, and race) or values (such as political beliefs). Below, I review the main findings of previous studies and propose several hypotheses:

3.2.1 Homophily Based on Gender

Gender homophily has been found to be present in social and professional networks (Louch, 2000; McPherson et al., 2001). The findings of previous studies suggest that males are more homophilous in tie formation (tend to interact with other males) than females do (Ibarra, 1992; Kleinbaum, Stuart, & Tushman, 2011). Particularly, Ibarra (1997) suggests that in workplace environments males show a high gender homophily by mainly interacting with their male coworkers. However, females tend to interact with their male peers rather than female peers to increase their chance for promotions and better job opportunities.

The recent studies about homophily based on gender warn that to study this phenomenon one should distinguish the professional relationships from personal relationships. Smith et al. (2014) found that both males and females show a high level of homophily in personal relationship networks, but females show heterophily in workplace environments. Given that the communications among the U.S. House Representatives can be regarded as workplace communications, I therefore propose:

H1- Gender homophily:

H1a: Ceteris paribus, both male Representatives and female Representatives show a high tendency in forming Twitter communication ties with male Representatives over time.

H1b: Ceteris paribus, both male Representatives and female Representatives show a high tendency in persisting Twitter communication ties with male Representatives over time.

Homophily Based on Race

Race is claimed to be the biggest divide in social networks in the United States, and is claimed to play a major role in structuring the networks in other ethnically diverse societies as well (McPherson et al., 2001). Similar to gender homophily, race homophily has been reported to have a twofold effect in network formation (Smith et al., 2014): First, in cases where the network ties are created based on personal relationships (e.g. close friendships), minorities (African Americans and Latinos) show a higher level of homophily than do Whites (Mollica, Gray, & Treviño, 2003). Second, in cases where the network ties are created based on professional relationships (e.g. workplace relationships), minorities show a lower level of homophily than do Whites (Ibarra, 1995). Similar to females, minorities in workplace tend to interact with Whites to pave their road for better job opportunities.

Therefore I propose:

H2- Race homophily:

H2a: Ceteris paribus, both White Representatives and ethnical minorities show a high tendency in forming Twitter communication ties with White Representatives over time.

H2b: Ceteris paribus, both White Representatives and ethnical minorities show a high tendency in persisting Twitter communication ties with White Representatives over time.

3.2.2 Homophily Based on Party Affiliation (Political Values)

Forming relationships based on political affiliation goes beyond workplace communications and can be even found in online dating relationships. For instance, a study by Huber and Malhotra (2014) revealed that "people find those with similar political beliefs more desirable and are more likely to match with them compared to people with discordant opinions" in an online dating community. In another study, Halberstam and Knight (2015) found that politically active Twitter users tend to interact with other users with the same political views. Conover et al. (2011) and Yardi and Boyd (2010) also found significant presence of political homophily in communication network of Twitter users.

Therefore I propose:

> H3- Political homophily:
>
> H3a: Ceteris paribus, Representatives from the same political party show a high tendency in forming Twitter communication ties over time.
>
> H3b: Ceteris paribus, Representatives from the same party show a high tendency in persisting Twitter communication ties over time.

3.2.3 Exponential-family Random Graph Model (ERGM)

The basic idea of ERGM is to find a model of a network formation process that maximizes the likelihood of an observed network (y) being created at some point in time in this process. Within this framework, one can obtain maximum-likelihood estimates for the parameters of a specified model for a given data set; simulate additional networks with the underlying probability distribution implied by that model; test individual models for goodness-of-fit, and perform various types of model comparison.

The class of ERGM has been developed on the basis of a Markov chain to include not only dyadic effects but also structural effects at the network level (Broekel, Balland, Burger, & Van Oort, 2014). The purpose of ERGM is therefore to describe parsimoniously the local selection forces that shape the global structure of a network (Hunter, Handcock, Butts, Goodreau, & Morris, 2008). Originally, ERGM is developed to address the complex inter-dependencies within relational data structures and to provide a flexible framework for these network structures (Handcock, Hunter, Butts, Goodreau, & Morris, 2008). In other words, ERGM provides a flexible approach for studying and incorporating observed network statistics such as degree distributions, mutual relationships, triangles, and cycles while also including exogenous attributes related to network vertices or even edges (ties) themselves. In ERGM framework, the observed network statistics are being considered as outcomes, and the goal of the model is to specify the process that leads to their joint distribution. In a nutshell, ERGM provides a statistical framework for evaluating alternative hypotheses about the processes that lead to the observed outcomes.

Researchers form a wide array of disciplines have employed ERGM to study the phenomena of interest. For instance, the social science researchers have employed ERGM to analyze the friendship networks (Goodreau, Kitts, & Morris, 2009; Lubbers & Snijders, 2007) and international political conflicts (Cranmer & Desmarais, 2011). Although the IS research has not yet directly benefited from these models, Chen et al. (2012) considered ERGM approach as one of the emerging research agendas in the realm of network analytics in IS discipline.

3.2.4 Separable Temporal ERGM (STERGM)

STERGM is an extension of ERG models for studying temporal dynamic networks. STERGM allows the researcher to create a temporal meta-network (a collection of cross-sectional networks over several discrete times) to study the temporal changes in the networks over time. The cross-sectional ERGM entails a single network, and a single model on that network. However, one of the key features of STERGM is that the processes for network formation and network dissolution are modeled independently. Therefore, the researcher could develop and test different hypotheses for tie formation and tie dissolution. STERGM uses two ERGM models at each time period: 1- an ERGM for modeling tie formation, and 2- an ERGM for modeling tie dissolution. It is worth noting that although STERGM is a recently developed approach, it has been employed for modeling dynamics of social interactions (Krivitsky & Handcock, 2014).

In the study, I start with an ERGM specification to study the presence of homophily based on gender, race, and political party in Mentions and Retweets networks of U.S. House of Representatives. Then, I employ STERGM to study the temporal changes in these two networks over a six month period.

3.3 Data and Method

This data set includes 3,685 Mentions (Figure 11) and 1,545 Retweets (Figure 12) by 370 U.S. House Representatives over the period between August 1st, 2013 to January 31st, 2014 (six months) and data about Representatives' party affiliation, gender, and race. To study the presence of homophily in Twitter communication network, I created two Twitter communication networks: Mentions network (a directed network

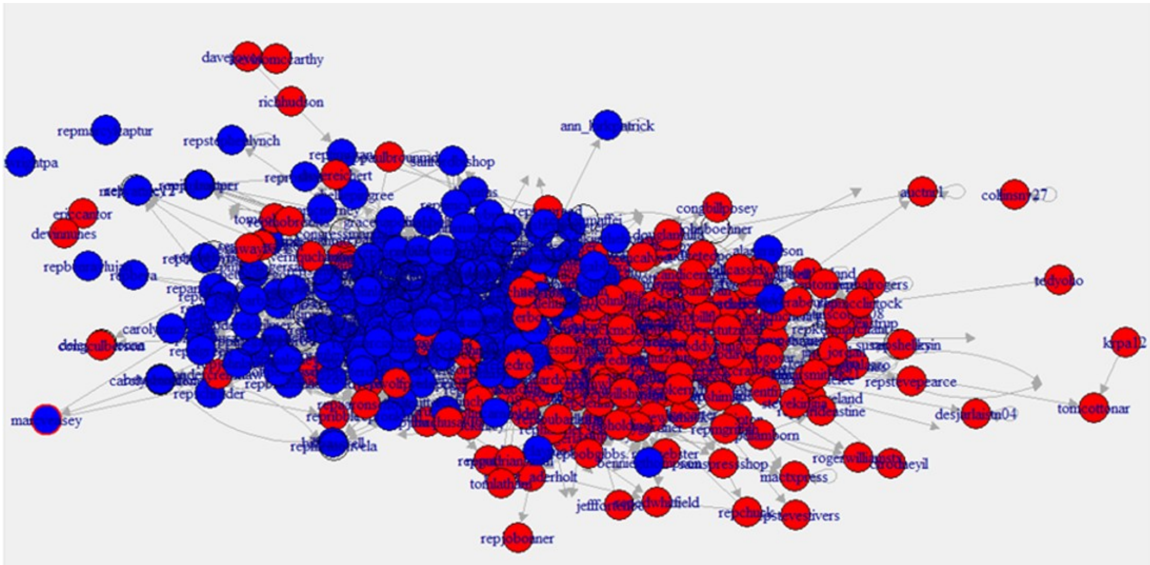

Figure 11. Mentions Network of Representatives (Blue Nodes Are Democrats and Red Nodes Are Republicans)

where a tie is created from Representative i to Representative j if Representative i mentioned Representative j) and Retweets network (a directed network where a tie is created from Representative i to Representative j if Representative i retweeted a tweet by Representative j).

I estimate an Exponential Random Graph Model (ERGM) that models a network as a function of individual, dyadic, and other structural characteristics. One of the key features of the ERGM approach is that this model treats the dyad as the unit of analysis. Therefore, for any pair of Representatives the model estimates the likelihood that a Twitter communication (retweet or mention) exists. In this case, I estimate how homophily based on gender, race, and political party affiliation affect the likelihood of a Twitter communication while controlling for network structure.

To study the impact of homophily on network evolution (tie formation and dissolution), I created two dynamic networks (meta-networks): The first meta-network is a

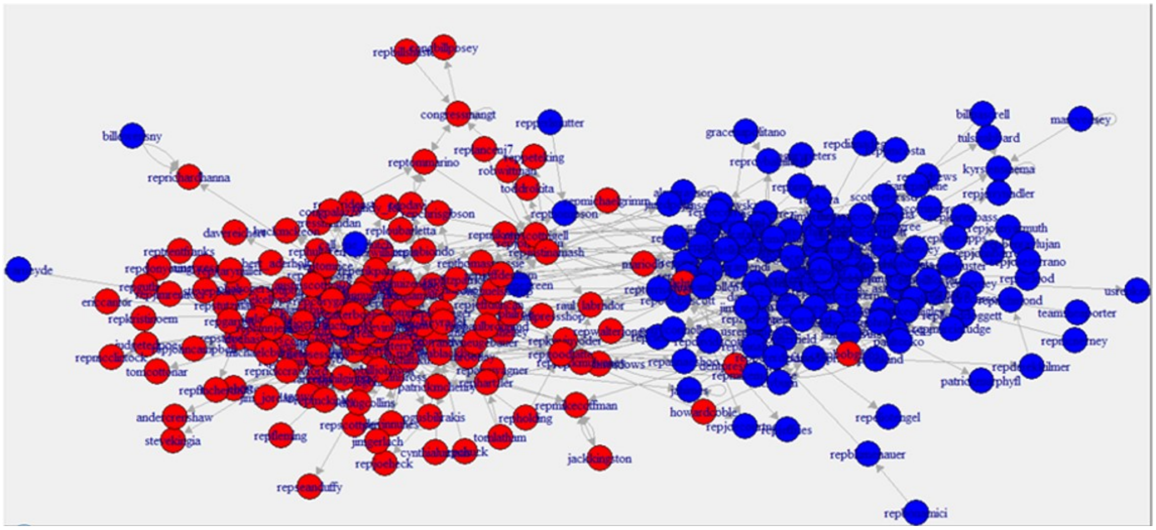

Figure 12. Retweets Network of Representatives (Blue Nodes Are Democrats and Red Nodes Are Republicans)

collection of six Mentions networks (one network for each month of the study), and the second meta-network is a collection of six Retweets networks (one network for each month of the study). I employed STERGM framework to study the formation and dissolution of ties in each meta-network.

3.4 Empirical Model

First, I employ the ERGM framework for the cross-sectional network over the period of six months as observed at a single point in time. Let $Y \subseteq \{1, ..., n\}^2$ be the set of ordered relations among n Representatives, let γ be the set of all obtainable networks and let y be the observed network where y_{ij} equals one if Representative i retweeted (mentioned) Representative j and zero otherwise. Therefore the distribution of Y can be parameterized in the form:

$$Pr_{\theta}(Y = y|X) = \frac{exp\{\theta \times g(y, X)\}}{c(\theta, X, \gamma)}$$

(3.1)

where g(y,X) is a function of network statistics with parameters θ, and $c(, X, \gamma)$ is the normalizing constant which is a summation over the space of possible networks on n nodes (Representatives), γ . That is:

$$c(\theta, X, \gamma) = \sum_{y' \subseteq \gamma} exp\{\theta \times g(y', X)\} \tag{3.2}$$

Since in this case I need to study the effects of homophily in network formation, I also incorporated X which is an array of dyadic attributes. That is, X_{ijs} equals one if Representative i and Representative j take the same value with respect to a given exogenous attribute s. For instance, if Representative i and j are both female or both male $X_{ij(s=gender)}$ equals one and zero otherwise. With this specification, the effects of differential homophily based on gender can be estimated (Hunter et al., 2008).

3.5 Results

I first present the results of the ERGM for both Mentions and Retweets cross-sectional networks of Representatives over the six month period of the study. The results of ERGM estimations (static network) are reported in Table 18. The coefficient in front of the term Edges in Table 18 refers to the logit of the number of observed ties in the network divided by the total number of possible ties. This term would allow us to control for the potential effects of density of the ties in the network. According to

Table 18, one surprising finding is that female Representatives show a higher tendency to interact with each other, while male Representatives show a reverse tendency to interact with each other. To be specific, female Representatives are exp(0.436)=1.547 times more likely to mention another female Representative in their tweets. Female Representatives are also exp(0.540)=1.716 times more likely to retweet another female Represenitaive's tweet. Since the coefficients for male Representatives are negative, male Representatives are more likely to retweet or mention female Representatives rather than other male Representatives. Another interesting finding of this table is about race homophily. In both Mentions and Retweets networks, African-American Representatives show higher tendency in communicating with other African-American Representatives (2.232 times higher in Mentions network and 1.906 times more in Retweet network). Latino Representatives seem to be more interested in mentioning other Latino Representatives (1.861 times more), yet they do not show the tendency to retweet their tweets. On the other hand, the White majorities in the Congress do not show a significant tendency in mentioning other White Representatives but they are inclined to retweet their tweets more than by chance.

With respect to party affiliation homophily, both Democrats and Republicans tend to establish relationships with peers from their own party. The tendency in interacting with peers from the same political party is higher for Republicans both in Mentions and Retweet networks. For both Republicans and Democrats, the effect of political party homophily is larger in Retweets network than in Mentions network. Last but not least, homophily based on demographic characteristics (gender and race) is more effective in Mentions network (the network in Figure 11) while homophily based on values and beliefs (party affiliation) is more effective in Retweets network (the network in Figure 12). This is also observable in force-directed graphs in figures 11 and 12

Table 18. ERGM with Maximum Likelihood Estimation Results

Variables	*Mentions* Network	*Retweet* Network
Edges	**-3.459*** (0.245)**	**-4269*** (0.232)**
Gender Homophily- Female	**0.436*** (0.096)**	**0.540*** (0.128)**
Gender Homophily- Male	**-0.426*** (0.053)**	**-0.173* (0.081)**
Race Homophily- White	0.029 (0.057)	**0.312*** (0.093)**
Race Homophily- African American	**0.803*** (0.151)**	**0.645*** (0.204)**
Race Homophily- Latino	**0.621*** (0.199)**	0.334 (0.312)
Party Homophily- Democrat	**0.390*** (0.134)**	**1.787*** (0.243)**
Party Homophily- Republican	**0.890*** (0.132)**	**2.754*** (0.264)**

Note 1: Standard errors are reported in parenthesis.

note 2: Since Representatives from the same state may communicate more often, this factor is accounted for in both models.

* Significant at 0.05, *** Significant at 0.001

that are created based on Fruchterman Reingold algorithm. The blue nodes and red nodes are further separated in Retweets network which indicates that the effect of homophily based on political party affiliation in larger in Retweets network than in Mentions network.

Table 19 reports the results of STERGM for Mentions meta-network.[15] The first

[15] According to (Krivitsky & Handcock, 2014), conditional maximum likelihood estimation (CMLE) is an appropriate estimation for cases where two networks are compared together.

two columns of estimates report the results for tie formation and tie dissolution in transitioning from August (time t) to September (time t+1). Since the data include network information for six months, there are a total of five transitions from the previous month to the next month. In each transition, one set of estimations for network formation and one set of estimations for tie dissolution are reported.

I first discuss the results for female Representatives: according to the results for Formation, the coefficient for female Representative is always significant and positive in all models. This indicates that female Representatives have a high tendency in establishing new communications with other female Representatives through mentioning them in their tweets. Furthermore since the coefficient for Dissolution is also significant for the most part, I conclude that female Representatives tend to persist their mentioning communications with other female Representatives over time. The negative coefficients for tie formation for male Representatives indicate that they have a low tendency in establishing a new communication with mentioning other male Representatives. However since the coefficient for dissolution for male Representatives is significant and positive for the most part (except in September -> October and December -> January), I suggest that those male Representatives who mention other male Representatives tend to continue this behavior over time.

According to the results of Table 19, White Representatives have a higher tendency in forming and persisting their Mention ties with other White Representatives for the most part (except in November -> December). Similarly, African-American Representatives have a high tendency in forming a new tie by mentioning other African-American Representatives in their tweets. However, African-American Representatives do not tend to persist this behavior over time. Latino Representatives have the tendency to form and persist a tie over time with other Latino Representatives.

Table 19. STERGM with Conditional Maximum Likelihood Estimation Results for the Mentions Network

Variables	August ->September		September -> October		October-> November		November> December		December> January	
	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution
Edges	-7.548***	-11.499***	-6.337***	-9.046***	-6.150***	-8.504***	-6.192***	-8.798***	-6.258***	-8.624***
	(0.171)	(0.963)	(0.102)	(0.496)	(0.103)	(0.354)	(0.105)	(0.354)	(0.106)	(0.324)
Gender Homophily-Female	1.343***	2.296***	0.792***	1.468***	0.712***	1.243***	0.554**	1.027*	0.692**	0.240
	(0.214)	(0.764)	(0.148)	(0.429)	(0.185)	(0.389)	(0.192)	(0.411)	(0.188)	(0.428)
Gender Homophily-Male	0.135	1.537**	-0.131	-0.655*	-0.591***	0.798***	-0.257*	0.803**	-0.319**	-0.042
	(0.140)	(0.633)	(0.093)	(0.377)	(0.107)	(0.269)	(0.114)	(0.273)	(0.109)	(0.291)
Race Homophily-White	0.617***	1.122*	0.442***	1.140**	0.244*	0.808**	-0.096	0.486	0.60	0.955**
	(0.156)	(0.726)	(0.092)	(0.424)	(0.120)	(0.303)	(0.122)	(0.314)	(0.115)	(0.342)
Race Homophily-African American	1.503***	1.129	1.306***	2.078***	1.094***	-0.273	0.967**	0.190	-0.258	0.236
	(0.122)	(1.198)	(0.203)	(0.571)	(0.325)	(0.763)	(0.277)	(0.898)	(0.458)	(0.771)
Race Homophily-Latino	0.913	2.171***	0.758*	-0.046	1.591***	1.007	1.190***	1.991***	0.038	1.971***
	(0.518)	(0.777)	(0.328)	(1.075)	(0.296)	(0.756)	(0.316)	(0.498)	(0.508)	(0.474)
Party Homophily-Democrat	1.258***	0.956	1.420***	0.261	0.597***	-0.105	0.923***	0.634*	1.192***	0.593
	(0.174)	(0.743)	(0.106)	(0.400)	(0.136)	(0.293)	(0.129)	(0.329)	(0.123)	(0.337)
Party Homophily-Republican	1.515***	0.898	0.841***	-0.428	1.181***	0.217	0.863***	0.567	1.009***	0.563
	(0.159)	(0.666)	(0.115)	(0.367)	(0.125)	(0.276)	(0.140)	(0.307)	(0.134)	(0.344)

Note: Standard errors are reported in parenthesis.

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

The coefficients for political party homophily reveal interesting findings. For both Democrats and Republicans tie formation coefficients are positive and significant over time. However, tie dissolution coefficients are not significant (except for Democrats in November -> December). This observation indicates that Representatives have a high tendency in creating new ties with their peers in their own party, yet they do not persist this type of online communication over time.

Table 20 reports the results of Retweets meta-network. Again, female Representatives tend to form new ties by retweeting other female Representatives. However, in Retweets meta-network the coefficients for tie dissolutions are not significant. That is, female Representatives do not tend to persist their retweeting behavior over time. Male Representatives do not have any tendency in forming or persisting ties with other male Representatives. Among Whites, African-Americans, and Latinos, African-Americans have a higher tendency in retweeting other African-Americans tweets.

Table 20. STERGM with Conditional Maximum Likelihood Estimation Results for the Retweets Network

Variables	August ->September		September -> October		October-> November		November> December		December> January	
	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution	Formation	Dissolution
Edges	**-9.002***** **(0.379)**	**-7.259***** **(0.238)**	**-7.774***** **(0.240)**	**-8.135***** **(0.879)**	**-8.464***** **(0.324)**	**-6.206***** **(0.464)**	**-9.493***** **(0.459)**	**-6.707***** **(0.802)**	**-8.621***** **(0.340)**	**-9.179***** **(1.255)**
Gender Homophily-Female	**1.132***** **(0.263)**	0.428 (0.377)	0.436 (0.235)	-0.081 (0.546)	**1.146***** **(0.279)**	0.078 (0.776)	**1.590***** **(0.288)**	0.815 (0.695)	**0.467*** **(0.245)**	-0.431 (0.679)
Gender Homophily- Male	-0.195 (0.175)	0.181 (0.237)	-0.217 (0.130)	-0.062 (0.398)	-0.193 (0.178)	0.090 (0.749)	0.027 (0.216)	0.473 (0.440)	-0.254 (0.138)	-0.160 (0.381)
Race Homophily-White	**0.526*** **(0.211)**	0.265 (0.143)	0.214 (0.147)	0.407 (0.527)	0.307 (0.203)	0.594 (0.544)	0.427 (0.234)	**2.894*** **(1.077)**	0.271 (0.154)	0.903 (0.671)
Race Homophily-African American	**1.367**** **(0.420)**	NA	**1.314***** **(0.270)**	**1.080**** **(0.710)**	0.401 (0.603)	0.094 (1.102)	**1.374**** **(0.423)**	NA	0.093 (0.463)	1.244 (1.179)
Race Homophily-Latino	**1.254*** **(0.604)**	0.626 (0.796)	0.829 (0.462)	NA	0.679 (0.726)	1.747 (1.107)	0.427 (0.234)	0.172 (0.944)	**0.883*** **(0.462)**	1.723 (1.276)
Party Homophily-Democrat	**2.521***** **(0.366)**	-0.082 (0.480)	**2.489***** **(0.231)**	0.341 (0.805)	**2.173***** **(0.315)**	0.430 (0.463)	**2.854***** **(0.438)**	0.272 (0.801)	**3.329***** **(0.331)**	0.209 (1.190)
Party Homophily-Republican	**3.210***** **(0.350)**	-0.785 (0.743)	**2.473***** **(0.228)**	-0.315 (0.744)	**2.767***** **(0.299)**	0.187 (0.463)	**3.113***** **(0.429)**	0.725 (0.800)	**3.256***** **(0.330)**	0.940 (1.122)

Note 1: Standard errors are reported in parenthesis.

Note 2: The estimation did not result in a value where NA is used.

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

The largest effect of homophily in Retweets meta-network can be observed in political party homophily. The coefficients for both Republicans and Democrats for tie formation are significant and positive over time. These coefficients are also larger than the coefficients in Table 20. This signals that homophily based on political party is more effective in Retweets meta-network than in Mentions meta-network. This finding is consistent with the results reported in Table 19.

Overall, thefindings support the majority of thehypotheses. With regard to gender homophily (H1a and H1b), female Representatives have a high tendency in forming and persisting their ties with other female Representatives. Such an effect was not observed in the group of male Representatives. With regard to race homophily (H2a and H2b), both Whites and minorities tend to form and persist their Twitter ties with Representatives with the same ethnical background. With regard to homophily based on political party (H3a and H3b), both Republicans and Democrats have a high tendency in forming ties with their peers from their own parties (H3a). However, they do not tend to persist these ties over time (H3b). Comparing the coefficients in tables 20 and 21 signals that homophily based on political party is more effective in Retweets meta-network than in Mentions meta-network. This is consistent with the findings of other studies (Conover et al., 2011). Discussion & Concluding Remarks

One of the most interesting findings of this study is related to the significant and positive homophily for female Representatives. Theresults differ from the results of the previous studies (Ibarra, 1992, 1997; McPherson et al., 2001) where the researchers reported the presence of homophily for males rather than females. Particularly, Ibarra (1997) reported that in workplace environments females tend to have higher interactions with their male counterparts to pave their road for promotions and better job performance. According to theresults, not only female Representatives tend to interact with other female Representatives, but also male Representatives tend to establish Twitter communications with their female peers as well. Furthermore, comparing ERGM and STERGM results confirm that female Representatives tend to not only establish online communication with other female Representatives, but also they tend to persist these communications over time. A comparison between ERGM and STERGM results for male Representatives shed further light into the dynamics of online communications in this group. Both ERGM and Formation STERGM suggest that male Representatives have a low tendency in mentioning other male Representatives in Twitter sphere. However, Dissolution STERGM reveals that those Representatives who indeed mention other male Representatives tend to persist this communication over time.

Again in contrast with the majority of the previous studies (Smith et al., 2014), I found that minorities (African Americans and Latinos) show the tendency to interact with each other even in a work-related environment. Among the ethnic groups, Latinos tend to start discussions with other Latinos through mentioning them in their tweets. However, these Representatives do not tend to confirm their peers by retweeting their tweets. Among Whites, African-Americans, and Latinos, African-Americans have the highest tendency in confirming their African-American peers by retweeting their tweets.

The homophily based on political party is significant and positive in both Retweets and Mentions networks. This finding provides another evidence for the widely known political segregation in The U.S. House of Representatives (McCarty, Poole, & Rosenthal, 2008). By comparing the effects of homophily based on demographics such as gender and race with the effects of homophily based on political party between Retweets and Mentions network, an interesting trend emerges. In Retweets network, homophily based on political party is the dominant mechanism of tie formation (Table 21). However in Mentions network, homophily based on demographics seem to play a more important role. Given that a retweet is the broadcast of another person's opinion and therefore a type of confirmation, it seems that Representatives tend to confirm tweets posted by their peers from their own party. However, a mention can be a form of discussion between the two entities and therefore Representatives tend to pick other Representatives with similar demographics to start a discussion with. This could justify the reason why homophily based on political party is dominant in Retweets network while homophily based on demographics is more dominant in Mentions network.

CONCLUDING REMARKS

Online social networks have been identified as the enablers of many changes in our societies. From enabling minorities to engage in social and political practices to allowing like-minded users to find and influence each other's decisions, online social networks have made profound impacts. As extensions to the current studies in the realm of societal impacts of online social networks, the three chapters in this dissertation attempted to discuss the impact of online social networks on policy-making process in a democratic political system. Although more research is needed to study the mechanism of influence, but the findings of the first chapter suggest that online social networks could help the Members of the U.S. House of Representatives to vote closer to the preferences of their constituents.

In the second and third chapters, the focus is shifted from Representative-constituent interactions to Representative-Representative interactions. The findings of the second chapter suggest that the online social networks could be regarded as enablers of political polarization as they allow the Representatives to frequently express their views either in favor of their own party or as an opposition to the other party. Furthermore, online social networks would enable the Representatives to listen even more to their peers on the same side of the aisle. This in turn would help them to be even more in favor of their own party or oppose the other party. The third chapter studies the network ties in online social networks. The findings of this chapter sheds light on the way Representatives interact with each other. Primarily when it comes to Representatives confirming each other in online social networks (in the form of retweeting), the Representatives' political party plays the major role.

Overall, the findings of these three chapters suggest that the Representatives become closer to their constituents in terms of the political orientation and at the same time become more polarized due to the unique features of online social networks. Given that getting closer to the constituents and becoming more polarized at the same time is counter intuitive, more studies would be needed to explain this phenomenon. However, one of the major causes of this phenomenon could be the impact of online social networks in shaping the political orientation of the constituents. That is, online social networks could have the same polarizing effects on the constituents as they did on the Representatives. When the constituents become more polarized, the Representatives should become also more polarized to better align with their constituents.

In this dissertation, chapters two and three shed light on two different features of online social networks that could enable political polarization: 1- polarization due to the content created in online social networks and 2- polarization due to the structure and the dynamics of network connections within online social networks. These two features of online social networks could help the constituents to become more polarized. At the same time, the mechanisms that were discussed in chapter one would enable the Representatives to better align themselves with the constituents. Therefore, the Representatives can be more aligned with their constituents and polarized across the two major parties at the same time.

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APPENDIX A

ESTIMATING WNOMINATE SCORES

To estimate WNOMINATE scores for Representatives, I 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 / 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 21 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. I 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 21. 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