Twitter Adoption in Congress: Who Tweets First?

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Abstract

Our general objective is to characterize the recent and well publicized diffusion of Twitter among politicians in the United States 111th House of Representatives. Ultimately, Barrack Obama, Facebook and peers matter when it comes to the propensity and speed of Twitter adoption. A basic analysis of the distribution of first Tweets over time reveals clustering around the President's inauguration; which holds regardless whether the adopter is Democratic or Republican, or an incumbent or newcomer. After we characterize which representatives are most likely to adopt Twitter, we confirm the widespread belief that Facebook and Twitter are indeed complementary technology. Given their perceived desire for accessible government, a surprising result is that Republicans are more likely to adopt Twitter than Democrats. Finally, using the exact dates of each adopter's first Tweet, we demonstrate that the diffusion of Twitter is faster for those representatives with a larger number of peers already using the technology, where peers are defined by two social networks: (1) Politicians representing the same state; and (2) politicians belonging to the same committees; especially so for those in committee networks. This observed behavior can be rationalized by social learning, as the instances in which the peer effects are important correspond to the cases in which social learning is relevant.

Keywords: Communication, diffusion of technology, political marketing, social interaction, social media, social learning.

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1 Introduction

The Library of Congress recently announced that all Twitter posts will be archived in their digital data collection[1]. Even if Twitter turns out to be a fad, it is hard to be skeptical of Twitter's historical relevance, as it represents a movement away from traditional media sources, such as newspapers and television, towards media that draws its material from the general population. Nowhere is the effect of Twitter more profound than in politics. Motivated by the desire for transparent government, Twitter is becoming increasingly popular among politicians as a way to connect with constituents. In general, social media can benefit both the politician and his/her constituents. Constituents can stay informed about issues that their representatives are working on, while representatives can garner grass-roots support for their policies and their overall brand. For our paper, we focus on the assumed benefit accrued to the politician and ask, which politicians adopt Twitter, and among the adopters, who will adopt first. Our main conclusion is that adoption is largely driven by some complementarity with Facebook use, while early adoption is largely driven by peer effects.

The setting for our study is the adoption of Twitter among all active members in the United States 111th House of Representatives. Under this setting, we first verify the common belief that Facebook and Twitter are complementary communications technology. A representative who has a Facebook account is significantly more likely to adopt Twitter. This result relies on the identification assumption that Facebook was adopted before the decision to adopt Twitter, which is supported by anecdotal evidence. Furthermore, we argue that the effect from Facebook is not simply because it may account for the constituents' underlying preferences for social media by noting that a large number of politicians take use Twitter from Facebook, and link their Twitter pages to their Facebook pages. When we look closer into this effect, we find that the Facebook effect does not differ across different types of representatives, based on age, party, and tenure; which, is suggestive that the positive spillover associated with Facebook is enjoyed uniformly across the sample of representatives. Our most surprising result from our analysis of Twitter adoption is that Democrats are less likely to adopt Twitter. Their advocacy of open government seems to contradict this non-adoption of Twitter. Furthermore, representatives are more likely to adopt Twitter after the 2008 congressional election if they received a high percentage of votes during that election; this suggests that Twitter adoption is more likely to be driven by a representative's desire to maintain existing constituent support, rather than advertising their platform and generating more support.

[1] April 14, 2010 at http://twitter.com/librarycongress.

In summary, Republicans who won by large margins and have Facebook accounts are the most likely to adopt.

After characterizing entry into Twitter, we are interested in studying how exactly the diffuses. In particular, how does peer adoption affect the speed of Twitter adoption? To answer this question, we use the date in which a representative's first Twitter message was posted as a proxy for the true date of adoption. With this information, we can identify the exact order, day-by-day, in which all of the adopters adopted. Using this granular time of adoption information, we consider two situations in which the representatives can interact. The first is through a *state network*, in that politicians that operate within the same state most likely deal with similar issues and are most likely to interact; and the second is through a *committee network*, in which politicians who sit in the same committee(s) are most likely to interact. Although we consider peers coming from both networks for our analysis, we believe that the committee network is a more realistic setting for social interaction[2].

Simple regression uncovers a significant and economically important peer effect, in that a standard deviation change in the number of peers belonging to the committee network accelerates Twitter adoption by 3 days. Given that our metric for the number of days it takes to adopt is on average 6, this effect is important. When we group peers based on party affiliation, we find divergence in peer effects across parties, in that Republican peers in a committee network have a significantly larger effect than that of their Democratic counterparts. In general, we argue that these delays are generated by behavior consistent with *social learning*. The peer effects are most pronounced when social learning is the most important, such as for representatives with little experience with social media and/or well-connected.

Representatives face uncertainty when they decide to adopt Twitter. There is no guarantee that Twitter will improve their image or help them pass along information to their constituents. However, they can resolve some of this uncertainty by consulting with their peers who have already signed up. This learning process within a social network[3] should be especially fast if the representative has access to a large sample of past adopters' opinions. Each piece of information brings the representative closer to learning the true state; and given that the decision to adopt by others is a positive signal for Twitter's merit, the option value of delay should subsequently decrease with the number of past adopters. That is, once a representative receives enough "good

[2] See Brock and Durlauf (2004) and Manski (2000) for surveys about emprical models with social interactions.

[3] Social networks are important for information diffusion. The study by Cohen, Frazzini, and Malloy (2008,2009) show that sell-side analysts provide much better recommendations about companies that they have alumni connections with.

news" signals through social interactions, its benefit from adopting Twitter (i.e. *opportunity cost of delay*) exceeds the benefit from waiting for more information from others (i.e. *option value of delay*)[4]. As more peers adopt Twitter, the number of future adopters that a representative can potentially learn from by waiting to adopt declines; so too should the incentive to wait.

The intuition behind "wait-and-see" learning is largely guided by the theoretical work by Caplin and Leahy (1998), Chamley and Gale (1994) and the theoretical extensions that followed[5]. If the past adoption decision of neighbors or peers has informative value, then a potential adopter has an incentive to delay his/her action so as to exploit the information externalities. But with enough information on hand, this incentive to delay should subside, so as to speed up the adoption of Twitter. Unlike standard models information externalities materialize via signals or actions alone, our story likely involves both, as social interactions upgrade the informational value of just observing the Twitter adoption among peers alone.

Our identification of peer effects is subject to the standard Manski (1993) critique. We first refute the claim that exogenous characteristics of peers are generating this effect by including the number of Democratic peers in the original regressions. Doing so does not change our results. Moreover, our results are robust to correlated effects associated with each network itself. Next, we acknowledge the fact that a large number of first Tweets were centered around Barrack Obama's inauguration, and omit those observations from our analysis; doing so does not weaken our results, but instead, increases the magnitude of the committee peer effect. The last concern we address is the role of unobserved heterogeneity, which could bias our peer effect estimates. Publicly available *ex post* Twitter usage statistics for each representative's URL are used to proxy for unobserved heterogeneity related to unobserved preferences and information, which are later shown empirically to have insignificant virtually negligible - in magnitude - relationships with the speed of adoption.

By exploiting information about timing into our analysis, we are able to analyze peer effects and social learning without the threat of simultaneity, in that the adoption activity among a representative's peers occurred (well) before his/her own observed decision. To some extent, this makes our paper very similar to Conley and Udry's (2010) empirical analysis of learning within social networks, who also exploit timing information[6]. What separates our work is our focus on the speed of adoption among adopters, while their focus is on the propensity to adopt. One advantage of

[4] Please refer to the appendix for further details.

[5] These theories have been used primarily to explain delays in investment of firms and government. See Chamley (2004) for a summary.

[6] Jackson (2008) remarks that timing information is a potentially powerful approach to avoid typical reflection problems.

their work though is that unlike our definitions of social networks, they are able to define networks exactly, in that surveyed agents identify who they communicate with.

Our goal of identifying social learning places this paper in a small but growing set of empirical literature. In addition to Conley and Udry, recent empirical applications of social learning include Morreti's (2010) analysis of learning in movie consumption, and Buera, Monge-Naranojo and Primiceri's (2010) estimation of learning in macroeconomic policy decisions.

Morretti identifies social learning using the idea that movie sales will react to past surprises based on the difference between *ex ante* expectations and realized outcomes. This identification strategy is based on the premise that Bayesian agents will update their beliefs only if signals are different from their prior and relies mostly on falsification tests to ensure that the effects are actually consistent with learning. Buera, Monge-Naranojo and Primiceri's (2010) take a different approach, and rely on a structural model of learning, whereby information across countries are spatially correlated, making Bayesian learning off of a neighbor's observed policy decision possible. Between the two approaches, ours is the most similar to Morretti's methodology, in that we attempt to separate the learning hypothesis from an alternative by confirming that the so-called learning effect is most pronounced when it should be. Our approach complements Morretti's work, in that our interpretation relies on the dynamic aspects associated with social learning, such as the trade-off between the option value and opportunity cost of delay, which will result in slow or fast adoption, depending on the extent of adoption among peers.

There are a few recent studies in political science that share the same setting as us. In the studies by Lassen and Brown (2010), and Williams and Gulati (2010), they share a general empirical strategy as us by analyzing which politicians adopt Twitter, based on politician and district characteristics. We however, are more interested in the relationship between Facebook and Twitter, and whether there exists complementarity between the two. Furthermore, our main contribution is the identification of peer effects in different social networks, which, we later conclude as being generated by social learning or more specifically, word-of-mouth diffusion. That said, our paper provides a more comprehensive characterization of Twitter diffusion. Moreover, our methodology may be applied to other settings for which social media is being adopted[7].

Within the realm of social networks in politics, a recent paper by Cohen and Malloy (2010) looks at the effect that social networks have on politicians' voting behavior. They identify alumni

[7] For example, Twitter has become an increasingly popular marketing tool for businesses, ranging from Best Buy to Zipcar. Moreover, a search on Amazon.com reveals at least a handful of business strategy books on how to utilize Twitter effectively.

networks that connects politicians to other politicians, politicians to firms, and networks based on seating arrangement in the Senate. Their identified peer effect can be interpreted as the incentive to support bills that the social network finds important (but not the individual voter himself), with the implied expectation of reciprocity in future bills that the individual may want passed. Note that in our specification of committee networks, the likelihood of social interaction among peers is high, while in their alumni networks, there is no obvious reason why they would necessarily interact.

The remainder of the paper is organized as follows. Section II outlines some basic information about social media and its relation to politics, followed by a detailed description of the data. Section III provides some simple characterizations of who adopts Twitter. Section IV investigates how peers impact the speed of Twitter adoption by focusing on the sub-sample of adopters. Concluding remarks are provided in Section V.

2 Background

2.1 Basic idea behind social media

Twitter is a recent micro-blogging craze, among the already saturated market of social media[8]; by the end of 2008, there were over 3 million Twitter users (Comm, 2010). The basic idea of Twitter is that those who have accounts can write short messages (up to 140 characters) that can potentially be read by thousands (or millions). That said, a Twitter user's main objective is often to attract as many followers as possible, and keeping existing followers interested in their Tweets by posting compelling content. Unlike its most famous cousins, Facebook and Youtube, users cannot post pictures or videos on their Twitter feeds; although, they can post links containing this content. Twitter has outshined traditional blogs because of its ease and simplicity; no longer do bloggers have to spend countless hours writing online content, when all they need is a few seconds to send a Twitter post via Short Message Service (SMS)[9] (McFedries, 2007). A Twitter user gets the most benefit by also following the content of others, as being a follower of a fellow Twitter user might generate some reciprocity in followings. That said, some of the most popular Twitter accounts are those who have many followers but only follow a handful of other accounts. Unlike the more traditional form of Blogging, Twitter users rely on the technology to market themselves as a quality brand, as opposed to a low cost way to generate advertising revenue. For example, the GOP Leader John Boehner has over 25000 followers and was following over 12000 users as of May 28, 2010.

Preceding forms of social media include MySpace, Real Simple Syndication (RSS), Flickr, Face-

[8] See Comm (2010) for a complete list and description of available social media outlets.
[9] See McFedries (2007) for further details.

book and Youtube, launched in 2003, 1999, 2004, 2004 and 2005. MySpace and Facebook are primarily social networking sites, although Facebook attracts mostly college educated people, while MySpace is well known for its members belonging to the music and film industry. Both have been used as venues for naked self promotion. In fact, it has become common practice for employers to evaluate job candidates by their social networking sites[10]. RSS allows Internet users to easily and effortlessly subscribe to their favorite Blogs, such as New York Time's Freakonomics or Financial Time's Undercover Economist. Flickr and Youtube specialize in publishing user generated photos and videos, respectively. They provide an easy way to share content that would otherwise be hard to share due to their file sizes. Moreover, with the spread of high speed internet, online photo albums and video streams are more accessible than ever. Successful and well known users in social media are known for integrating and combining multiple sources to cross market their brand. Facebook users can Tweet and share Youtube videos, Youtube users can include links to their MySpace videos for viewers who want more content and Facebook users can submit their Twitter messages through a Facebook Application. Finally, Twitter is an effective way of introducing a large audience to the same user's Blog. Drawing on popular culture, Apple super-fan iJustine and video Blogger Kevjumba have successfully capitalized on multiple social media platforms to promote themselves at viral levels.

2.1.1 Past research on social media in politics

Although there exists no (political) economy or management literature about Twitter use in politics, research in this area has become increasingly popular in other fields[11]. Virtually all of the past research is concerned with answering the question: "How is Twitter used?" Used as motivation for our study, Golbeck, Grims and Rogers (2010) analyze the content of Tweets among all U.S. politicians and find that 53% of all Twitter content generated by them contains information, which they define as statements that contains links, positions on relevant issues, or resources; this finding contradicts the popular criticism that Twitter is simply an online environment that incubates hipster narcissism (McFedries, 2007). Some view the information provided by politicians through social media as being useful in two manners, one in which politicians tell us what they want us to hear (a.k.a. outreach), and one in which information actually has value and keeps government honest (a.k.a. transparency).

[10] See article Employers Look at Facebook Too. *CBC News*, June 20, 2006.

[11] For instance, there is research on the content and conversations within Twitter (Honeycutt and Herring, 2009), Twitter as word of mouth (Jansen et. al., 2009), and Twitter's relationship with social networks (Java et. al., 2007; Krishnamurthy, Gill, and Arlitt, 2008),

The research on Twitter in politics is nested within existing research about the evolution of congressional communication over time[12]. Their conclusions overwhelmingly point to the importance of the Internet and communication. To summarize, the Internet has improved interactions between politicians and voters, and as a consequence, those who embrace the technology have seen much success; with better communication, comes better mobilization of voters who support for a representative's agenda.

Social media in general has played an increasingly large role in politics around the world, especially so after the Franking Commission[13] permitted unrestricted use of social media in congress. For example, Williams and Gulati (2009) find that the percentage of active Facebook users among candidates in the 2006 and 2008 elections increased from 17.8 to 69.9 percent. Other authors have found that internet communications and social media matter in politics (Gibson et al, 2003; and Smith and Rainie, 2008). Our paper takes as given that social media is relevant. During the 2008 Presidential race, Barrack Obama devoted nearly 100 staff just to maintain his image on social media outlets[14]. Twitter also has the power of organizing large movements, such as the response of Mir-Hossein Mousavi's supporters to Iran's disputed and controversial election outcome in 2009[15]. Social media has proved to be among the most important PR tools in modern politics, and continues to do so. Perhaps the most fitting quote to describe Twitter adoption in politics is by Ivor Tassell of the Globe and Mail (September 4, 2008)[16]: "*Like rats scurrying up the ropes before an ocean liner departs, politicians have sharp noses for knowing when to hop aboard a trend.*"

2.2 Data

Our cross-sectional sample of observations consists of all active congressmen and women of the 111th House of Representatives. To obtain detailed information about each representative, we use a combination of the information provided on their own personal websites, the Biographical Directory of the United States Congress, as well as Wikipedia. Using these sources of information, we can find out how long each representative has been in office, the state and district he/she represents, how old they are, their gender, race, religion, education and previous occupation before serving the public. We augment this information with data from the 2000 U.S. Census for the districts that they represent, such as the population, median income and race distribution of their corresponding districts.

[12] To name a few, refer to Gulati (2004), Lipinski and Neddenriep (2004) and Oleszek (2007).
[13] Body of government that regulates Congressional Mass communication.
[14] See the article Sweet to Tweet. *The Economist*, May 8, 2010.
[15] See the article Iran Protests: Twitter, the Medium of the Movement. *Time Magazine*, June 17, 2009.
[16] The authors first discovered this quote on the blog on Twitter analysis, http://blog.mastermaq.ca/.

Other important information in our data is each representative's use of social media, such as MySpace, RSS, Flickr, Facebook, Youtube, and Twitter. Representatives often have a section on their homepage that contains icons that link their personal website to corresponding media sites. With the exception of Twitter, we try to avoid using Internet searches for the representative's social media portals, as there is no guarantee that those sites are actually endorsed by the representative. Twitter, on the other hand, has a verification system that ensures identity authenticity. For each representative who uses Twitter, we extract the date in which their first public message was posted. This exact date provides us a valid proxy as to the time in which the representative adopted Twitter, as an active Twitter user is almost surely one that Tweets. Unlike Facebook, there is no value in being a passive user.

For each representative, we also observe which committees he/she belongs to. Representatives reveal which committees they would like to become members of, which is followed by a formal vote by the House. A representative's underlying interests and experience are major determinants as to which committees he/she will end up in. Moreover, each committee is chaired by a Democrat, and consists of disproportionately more Democrats than Republicans, so as to reflect the current proportion of Democrats in the House of Representatives. In our data, there are a total of 23 committees, each with a specific mandate and jurisdiction, that a representative can potentially be a member of[17]. On average, representatives belong to about 2 committees. The maximum number of committees representatives in our sample belong to is 4. Committee information will be important in the last section, as we attempt to establish relevant social networks between politicians. A histogram shows that the distribution for the number of committees is centered at the mean. Moreover, the distribution seems to be invariant to whether the politician is a Twitter user or not.

All of the information about Twitter adoption was collected on May 24, 2010. There is very little entry into the Twitter platform in 2010, which is suggestive that the diffusion of Twitter was stabilized by the time data was collected[18].

2.3 Major events and Twitter adoption

To analyze the distribution of Twitter adoption around important economic and political events, we calculate the number of days between an adopter's first Tweet, and the event. Negative values imply days before the event, while positive values imply days after the event. We then graph the distribution of these values. We focus our attention on five well publicized events:

[17] Note however that our data falls short of identifying the subcommittees that each representative belongs to.

[18] However, the authors will keep a careful eye on Twitter adoption around the upcoming congressional election in 2010.

1. Barrack Obama's first Twitter post on April 29, 2007.
2. The financial bail-out on October 3, 2008.
3. The 2008 Election on November 4, 2008.
4. Barrack Obama's inauguration on January 20, 2009.
5. Health care vote on March 22, 2010.

The first histogram looks at the diffusion of Twitter after Barrack Obama's first Tweet. All but one of the representatives in our sample adopted Twitter after Barrack Obama made the first leap. In fact, a large proportion of them followed suit well after Obama's first Tweet. This diffusion pattern has characteristics of social learning, in that adoption is slow initially since potential users are delaying entry so as to exploit informational externalities that those preceding them may provide.

Surprisingly, there is not much Twitter adoption prior to the 2008 Election. We expected there to be a large number of representatives adopting the technology for their campaigning efforts, as Barrack Obama did. Instead, much of the adoption is concentrated after the election. In fact, much of the entry into Twitter technology is centered around Barrack Obama's presidential inauguration ceremony. When we look at the distribution of entry into Twitter over time across parties, we see that this pattern is not exclusive to the Democratic party. In fact, it would appear as though a greater concentration of Republican Twitter adoption is centered around this date. We suspect that politicians may be induced to participate in Twitter around this time to write a short message either congratulating the new President, or provide commentary about the President and his policies.

An alternative interpretation of this observed phenomenon is that the time of inauguration also corresponds to the time that new representatives assume office. Therefore, this clustering should only happen for new representatives as incumbents entered office well before January 20, 2009. However, when we look at the distribution of entry into Twitter by newcomers and incumbent separately, the two types of representatives share very similar distributional patterns.

3 Characterizing Twitter adoption

This section is meant to characterize the representatives who choose to use Twitter. As no previous study has done so, we feel it is meaningful to conduct this exploratory analysis. The analysis is motivated by the question as to the complementarity between Facebook and Twitter. With the integration of Twitter applications (i.e. "Apps") in Facebook, we would expect there to be some complementarity between these two sources of social media. Our analysis confirms that indeed this conjecture is true. Moreover, the complementarity seems to be felt uniformly across representatives of different age, party affiliation and tenure.

3.1 Identification strategy

We use the full sample of representatives to conduct this analysis. What we are interested in is the propensity to Tweet, conditional on a number of representative specific variables The analysis is carried out using a simple Probit model where the adoption of Twitter is represented by a 0/1 dummy variable. A number of co-variates are included to control for representative specific heterogeneity. The independent variables fall under three main categories. First, we have information about the representative, such as gender, race, age, tenure, party, religion, education and previous occupation. We control for religion, education and previous occupation by representing them using categorical variables; consequently, there is no clear interpretation for the coefficients associated with these three variables. The second set of variables are regarding information about the representative's constituents, such as the district's population, income and demographics. Finally, the third set of variables characterize the representative's usage of older social media, such as MySpace, RSS, Flickr, Facebook and Youtube. It is these set of variables that we are most interested in, as they will allow us to establish complementarity between Twitter and other media.

One important qualification for incorporating the usage of other social media as independent variables is that their adoption decision was made before the decision to adopt Twitter. Although Facebook does not publicly make available the date in which each politician first became members, for nearly all Twitter adopters, there is evidence that Facebook was an important campaigning tool as early as the 2006 congressional elections (Williams and Gulati, 2009). Another important identification assumption is that all Twitter adopters who also use Facebook adopted Facebook at a time when they did not anticipate the launch of Twitter (two years later). This way, we rule out inter-temporal correlation of unobserved heterogeneity among forward looking politicians. Relaxing these assumptions is left for future work once better data about Facebook diffusion becomes available[19].

[19] The challenge with obtaining accurate Facebook diffusion data is that the dates in which representatives became members are not readily available due to privacy concerns. Moreover, it was only recently that Facebook users were able to post public status updates on their wall in the same spirit as Twitter. In general, getting good information about Facebook usage will be hit or miss, depending on how strict a representative's privacy settings are set.

3.2 Main results

Politicians that represent populated districts are more likely to adopt Twitter, as the impact of having Twitter as a marketing tool is significant if their audience is large and captive. One interesting (and surprising) result is that Democrats are less likely to adopt Twitter, despite Barrack Obama being an avid cheerleader for social media and transparent government. It is possible that Republicans view the adoption decision as one of strategy. Much like vertical competition between rival firms, Republican's may feel pressure to compete with Democrats in the arena of perceived openness.

We confirm that representatives view Twitter as a complement to Facebook. Facebook status has a positive and significant impact on the propensity to use Twitter. Although the other social media have positive effects on Twitter use, they are not quite as significant, which makes sense as Facebook has made the strongest effort to establish compatibility between the two. Alternatively, Facebook might be an indicator of the constituents' comfort with online communities. We cannot definitively rule out this alternative explanation, however, browsing through the Twitter pages confirm our intuition, as a number of representatives post Twitter messages using Facebook, while advertising their Facebook pages on their Twitter page; representatives are certainly taking advantage of these explicit synergies.

3.2.1 Does the complementary Facebook effect apply to all representatives?

We are interested in determining whether certain types of representatives are more likely to take advantage of the synergies that exist between Facebook and Twitter. For instance, if a representative already has a Facebook account, posting Twitter feeds can be done easily within the Facebook account; thereby saving the representative some time and effort.

The data tells us that there is no discernible pattern with respect to Twitter adoption and Facebook use interacted with age, tenure or party affiliation. From the estimated coefficients, one may conjecture that the marginal effects of these interacted terms are close to zero and/or statistically insignificant. Implementing the Ai and Norton (2003) technique for calculating marginal effects, we verify this conjecture. The marginal effects for Facebook interacted with age, tenure and party affiliation generate z-statistics of 0.12, 0.83, and 1.23 and magnitudes of 0.00079, 0.0054, and 0.079 respectively[20]. Therefore, the Facebook complementarity does not apply to a specific subset of politicians, but instead, applies quite generally to all.

[20] More detailed results are available from the authors upon request.

3.2.2 Is Twitter being used to generate new support or maintain existing support?

In the political science literature, it has been argued that social media is an important technological campaign innovation. We wish to look deeper and establish whether representatives use Twitter as a means to generate new constituent support, or maintain support from existing constituents. Intuitively, Twitter can facilitate both objectives, in that it can help representatives advertise their political platform to (potentially) large audiences in concise and sharp messages, or keep their existing supporters posted with recent activities, bills, and thoughts. This question is not answered directly, but we can infer the answer based on whether representatives are more or less likely to adopt when they won the 2008 congressional districts by large margins. The existing data is augmented by each representative's 2008 vote percentage. After including this new variable to the original Probit model, we find that the percentage of 2008 votes for a representative is positively and significantly associated with the propensity to adopt Twitter among representatives who adopted Twitter after the election; this effect is small and insignificant for those who adopted Twitter before the election, as one would expect. This result suggests that the incentive to adopt is tied to the existing support from voters, and that campaign considerations are actually not that important.

4 Characterizing the speed of Twitter adoption

For this part of our analysis, we focus on the sub-sample of politicians who adopted Twitter by the time of data collection. We are particularly interested in studying the speed of adoption and the role that peer effects play. Do peer effects speed up or slow down the adoption process? As the descriptive section showed, there is quite a lot of variation in *when* adopters adopted. Much of this variation can indeed be explained by variation in peer adoption. To establish this result, the next sections provide a simple identification strategy, followed by the key results. In the end, we find that peer effects matter, and these effects are consistent with those that would be generated by social learning.

4.1 Identification strategy

The data allows us to identify the exact date of each Twitter adopter's first Tweet. Therefore, we can identify how long it takes an adopter to adopt, as well as who adopted Twitter before him or her. We consider two possible social networks for which peer effects can diffuse through. The first one is the network of representatives within the same state, which we call the state network. Presumably, representatives within the same state will most likely care about similar issues and therefore, more likely to interact with one another. Our second definition is the network of representatives that belong to the same committees, which we call the committee network. Using these two social networks, we can define the $Committee\_peers_i$ as the number of peers that already adopted Twitter before representative i within his/her committee network, and $State\_peers_i$ as the number of peers that already adopted Twitter before i in his/her state network.

With these constructed variables, we can run the following regression[21]

$$Days\_to\_adopt_i = \alpha + \beta \cdot Committee\_peers_i + \gamma \cdot State\_peers_i + \boldsymbol{\delta} \cdot \boldsymbol{X}_i + \varepsilon_i$$

where $Days\_to\_adopt_i$ is the number of days past since the most recent adoption of Twitter by some other representative $j \neq i$[22]. For example, if representative A adopted on January 1, 2009, representative B on January 10, 2009, and representative C on January 31, 2009, we set the dependent variable for B and C to be 9 and 21 respectively. Consequently, the dependent variable is undefined for the very first Twitter adopter, as he was preceded by no other Twitter adopting representative. It is assumed that each representative is aware of all those who has already adopted before him/her, since politicians who adopt Twitter are publicly identified through Internet searches or http://tweetcongress.org. How soon a representative adopts relative to the most recent adopter is conjectured to depend on the peers around him/her as well as exogenous district and representative specific characteristics, $\boldsymbol{X}_i$. The vector $\boldsymbol{X}_i$ consists of the same independent variables as in the earlier analysis about Twitter adoption, such as information about the representative, his/her propensity to adopt other social media, as well as information about the represented constituents. We maintain the earlier identification assumption that the decision to use MySpace, RSS, Flickr, Facebook and/or Youtube were made well before deciding to add Twitter.

We include the two peer definitions in the same regression as the peers from both groups are unlikely to coincide, as committee members tend to be quite diversified. A simple scatter-plot shows that there is no clear pattern between the two variables. Having both in the regression when we are trying to understand and explain the results. There more variation in $Committee\_peers_i$ than $State\_peers_i$ largely because each representative belongs to a different number and set of committees that themselves are quite diverse. For instance, $Committee\_peers_i$ can be as much as 62, while $State\_peers_i$ is at most 21 in our sample. Representatives who do not belong to any

[21] An alternative specification using a proportional hazard model was also used. Results are qualitatively the same, and therefore, omitted in this version.

[22] An earlier draft of this paper used the number of days past Barrack Obama's first Twitter post. There were many issues with this measure, such as the fact that the relationship between the number of peers and the dependent variable was trivially defined.

committees will have $Committee\_peers_i = 0$.

Although representatives often state their preferences for which committees to belong to, whether or not their requests are actually honored depends largely on their qualifications and constituents' interests. Ultimately, our committee network is valid provided that committees are not formed *ex ante* with social media considerations. The state network is even less likely to be endogenously determined, as candidates often choose to represent districts they already live in[23].

As in most studies about peer effects, there is a potential identification problem associated with simultaneity (reflection problem); that is, if say two representatives make the decision to on how soon to adopt Twitter, the peer effect on when to adopt will be biased as the timing decision will be a non-linear function of both representatives' unobserved heterogeneity. We overcome this challenge by using the fact that the number of peers associated with i is based on the number *before* i adopted. Therefore, at the time that i decided to adopt at $Days\_to\_adopt_i$, his/her peers have already made their decisions in the past periods. As such, we can treat the two definitions of i's peers as being i's observed state variable (that will not subsequently be affected by his/her decision).

Even though simultaneity is unlikely to be an issue, we still need to ensure that the "endogenous" peer effect[24] based on past adoption within a network is not confounded by other factors within a network, such as exogenous characteristics within a network (*exogenous peer effects*), deterministic behavior within a network (*correlated effects*), the size of the network and unobserved heterogeneity.

4.2 Main results

The key takeaway from these estimates is that the peer effects within a committee network matter. They have a negative effect on the days to adopt, which means that a representative who belongs to a committee that increases in size by one standard deviation will adopt Twitter 3 days sooner. Considering that the average value for the dependent variable is about 6 days, this estimated effect is quite important. In fact, this result is robust to specifications that contain exogenous information about the committee, such as the number of peers who are democrats, and committee dummies (over 20 of them). We also verify that the peer effects are robust to the size of the social network as well as the month-year time of adoption[25]. When the regressions are repeated using the percentage

[23] For example, a quick overview of our data reveals correlation between the city where a representative's most recent degree was earned, and the region that he/she overlooks.

[24] We are using the same terminology as Manski (1993). Note however, our data structure avoids the reflection problem, hence, endogeneity is encapsulated by quotations.

[25] We define this using time dummies for each month-year. This way, we can get multiple observations for each time specific control.

of adopting peers within a network, we find that a standard deviation change in the percentage of observed peer adopters in a committee network accelerates the adoption of Twitter by 3 days as well.

To some extent, these estimates hold their own against the standard Manski critique. As politicians rarely change their party loyalties, which are formed well before they enter office, we expect the number of Democrats within a given network as a good source of exogenous variation across state and committee affiliations. Moreover, there should be no correlation between a representative's unobserved preference for Twitter and his/her peers' party loyalties. Although we have a number of other exogenous variables to choose from, we choose peers' party affiliation as it is an significant and important determinant of both the propensity, and speed of Twitter adoption. An alternative source of variation is the number of Facebook users among peers. We believe this measure though is not appropriate, as it might be correlated with unobserved determinants of Twitter adoption speed through positive spillover carried through network effects within Facebook and synergies between Facebook and Twitter.

From our estimates, we see that an increase in the number of Democratic peers within the same social networks speeds up the Twitter diffusion process. This result itself is interesting, since the dummy variable for whether an individual is Democratic or not has the tendency to delay entry into Twitter technology. We suspect that much of this effect is driven by the Republicans' desire to match the general transparent government ideology propagated by the Democratic party.

There are also concerns of correlated peer effects, in that members in the same social networks behave some deterministic manner. However, the peer effect from committee networks is robust to the specification that contains committee specific dummy variables.

Note however that peer effects are not as strong in state networks, as their estimates are quite noisy; this null result suggests that social interactions are more prevalent in committee networks, rather than state networks.

Descriptive analysis revealed that Twitter adoption was clustered around the time that Barrack Obama was sworn into office, on January 20, 2009. We want to avoid the possibility that the peer effect is artificially generated by representatives who adopted Twitter simply to lend their support to the new President, not because of some learning mechanism. To overcome this identification challenge, we repeat the same regressions as above, except by omitting observations for which Twitter was adopted within 25, 50 and 100 days before/after the day of inauguration. This way, our sample is most likely representative of a population of Twitter adopting politicians who were not influenced by the historically significant event.

The peer effect for both remains significant and important as we delete more and more observations of Twitter adoption centered around the inauguration date. In fact, the peer effect becomes more significant with the omission of observations for the definition based on common committee membership; ultimately, our peer effect associated with the social networks formed by committees is robust to the Obama effect.

When peers are identified as being Democratic or Republican, the adoption speed is much faster for those in committee networks with a large number of Republican adopters, rather than Democratic adopters. It appears as though the representatives are more likely to conform with Republican Twitter users, and differentiate themselves with Democratic Twitter users.

Population speeds up the adoption of Twitter, while income slows down the adoption of Twitter[26]. Being a female African-American representative in a predominantly black district speeds up the adoption rate. Those who earned their most recent degrees from an Ivy League school will also adopt Twitter sooner. A surprising result that complements our analysis of Twitter adoption is that among adopters, Democrats tend to adopt Twitter at a slower rate; despite the party's general ideology of more open and transparent government. Older politicians adopt Twitter sooner, but not experienced politicians. Finally, as one would expect, Facebook and Youtube's complementary effects also materialize in faster adoption.

4.2.1 Social learning and the speed of adoption

The previous section demonstrated that the speed of adoption actually accelerates with the number of past adopters in the same committees. This result can be rationalized by social learning regarding Twitter's merits. Adopting Twitter carries a lot of uncertainty, as the merits of it as a marketing tool are still yet to be fully discovered. Some constituents might welcome the perceived openness that Twitter offers, while others might simply view Twitter as a venue for narcissism and undesirable advertising. Because Twitter is a fairly new, politicians are unlikely to know the proportion of constituents who will react positively to their decision to adopt Twitter. However, this uncertainty can be mitigated through social interactions, whether they be with fellow committee members or politicians representing neighboring districts. Via word-of-mouth, a representative can continually update his or her belief about Twitter's merit by communicating through social interactions with those who have already adopted the technology.

[26]This result initially seems odd as there is evidence that Internet adoption is more prevelant among wealthier Americans. However, Internet use decreases with income. See Goldfarb and Prince (2008) for further details.

An alternative explanation is the existence of network effects in Twitter. Part of Twitter's appeal is the ability to have (public) conversations with fellow users. Therefore, the value of the Twitter communication platform increases as the online community grows. This means that a representative may wish to adopt sooner if it observes a large number of peers who have adopted, so as to exploit the network benefits of Twitter.

We attempt to disentangle these two explanations by stating two predictions, which are jointly unique to learning.

1. Learning is important to representatives with no prior experience with a similar social media outlet, such as Facebook.

2. Learning is important to representatives who are more well connected, such as those who have a long tenure in the House of Representatives.

Because Facebook shares a number of similarities with Twitter, such as the ability to post short public feeds, a Facebook user should already some information about how effective Twitter could be as a marketing tool. So our estimates are consistent with learning if those who already have Facebook have little to no reaction to what their peers are doing; conversely, those who have not adopted Facebook should react the most to what their peers are doing. Social learning theory should in fact generate an *opposite* prediction to one generated by network effects, given that Facebook and Twitter are shown to be complements in the first set of results; Facebook users should see a greater benefit of adopting Twitter when a large number of peers have already adopted, as the complementary technology will allow them to pool the network effects of Twitter into Facebook, and vice versa. That said, one simple way to test for this hypothesis is to run the following regression[27]

$$\begin{aligned} Days\_to\_adopt_i \quad = \quad & \alpha + \beta \cdot Committee\_peers_i + \gamma \cdot State\_peers_i \\ & + \zeta \cdot Committee\_peers_i \cdot No\_Facebook_i + \lambda \cdot State\_peers_i \cdot No\_Facebook_i \\ & + \boldsymbol{\delta} \cdot \boldsymbol{X}_i + \varepsilon_i \end{aligned}$$

and test whether $\zeta < 0$. First, this regression produces an F-statistic of 5.36 for the hypothesis $\beta + \zeta = 0$, which is rejected at 5% significance. Most importantly, $\hat{\zeta}$ is negative and significant at a 10% level (for the hypothesis that $\hat{\zeta} < 0$). There is certainly evidence that the adoption of peers

[27] We only focus on the interactions with the committee peer effects as the state peer effects are shown, despite being of the correct sign, to be statistically insignificant.

matters *more* to those who have not used Facebook before, in that the peer effect leads to an even faster adoption of Twitter for those unfamiliar with Facebook.

Social learning regarding non-essential issue like Twitter should require face-to-face communications between representatives[28]. The probability of interacting with others in person should increase as for those who are more connected. Presumably, those who have been in office the longest should have had the most opportunity to develop these necessary social connections. To test this hypothesis, we use

$$\begin{aligned} Days\_to\_adopt_i &= \alpha + \beta \cdot Committee\_peers_i + \gamma \cdot State\_peers_i \\ &\quad + \zeta \cdot Committee\_peers_i \cdot Tenure_i + \lambda \cdot State\_peers_i \cdot Tenure_i \\ &\quad + \boldsymbol{\delta} \cdot \mathbf{X}_i + \varepsilon_i \end{aligned}$$

and test the hypothesis $\zeta < 0$. The joint hypothesis $\beta + \zeta = 0$ is not as strong as the first test with an F-statistic of 2.4, but is still significant at a 15% level. Aso note that $\hat{\zeta}$ is negative, but not significant. We take this as weak evidence against the alternative that $\zeta > 0$. Here, the peer effect leads to faster adoption of Twitter among those with long tenured careers in the House of Representatives.

In summary, these test results collectively support the social learning story. The peer effect is most pronounced in cases for which social learning matters, such as cases in which a representative has little experience with social media and/or is most likely to be well-connected.

4.2.2 The role of unobserved heterogeneity

While we can control for committee or state specific effects, controlling for individual level heterogeneity is virtually impossible with the data on hand. Unobserved heterogeneity could lead to estimates that overstate the importance of peer effects, when in reality, Twitter adoption is instead driven by underlying preferences or knowledge about constituent support for Twitter that as observers, we are unaware about. We can, however, demonstrate that there are no patterns between the speed of adoption and some *proxy* for an unobserved preference or information Twitter. To resolve our concerns, we first outline two main sources of unobserved heterogeneity:

1. A representative may have strong or weak preference towards Twitter, that cannot be captured by observed variation.

[28] It seems unlikely that a representative will make a long distance call to another representative to inquire about Twitter.

2. A representative may have knowledge about the social impact they could have on Twitter, that cannot be captured by observed variation.

To find a proxy for these sources of unobserved heterogeneity, we extract more data from each representative's Twitter page on May 31, 2010. From their pages, we are able to observe usage and social impact statistics, such as the total number of Tweets, the number of other users the representatives are following, and the number of other users who are following the representatives. The first two are statistics generated by levels of activity, in that a representative has to choose to Tweet and choose to follow. Those that are more active, must be so because they receive utility from Twitter. Alternatively, representatives who choose to adopt Twitter may do so because they *ex ante* anticipate receiving strong support and enthusiasm from their constituents. So assuming that their predictions are accurate, the number of followers might proxy for this knowledge, as researchers, we are naive about.

By adding this information to our data, we can calculate the number of Tweets, followings and followers per day for each representative. For example, to calculate the number of Tweets per day, we calculate the total number of days as an active Twitter user to be the number of days between their first Tweet and the day we collected this new data. This value provides us a good approximation as to the level of activity per day, as representatives typically post the same number of Tweets per day. Similar constructions are used for the number of followers and following per day.

The day of entry into Twitter has economically small effect on the *ex post* levels of Tweets, following, or followers. A one standard deviation change in the days to adoption leads to an insignificant drop in Tweets by 0.004, increase in followers and followings by 0.2 and 0.08 respectively. Considering that the average number of Tweets, followers and followings are 146, 2618 and 408, there is no meaningful relation between these *ex post* proxies for unobserved heterogeneity and the speed of adoption.

5 Discussion

5.1 Summary

In this paper, we offer new insight into Twitter use in politics. Our analysis goes beyond the status quo by attempting to explain in detail, the diffusion process of Twitter. Using detailed data on each active politician in the 111th House of Representatives, we are able to characterize those who adopt Twitter, and among those who adopt, which ones adopt sooner.

Facebook plays an important role in Twitter adoption, as it has positive externalities for Twitter use. Therefore, one may view Facebook not as a substitute to Twitter, but instead, a complement. We also find that despite the Democratic platform of transparent government, Democrats are less likely to adopt Twitter than Republicans. This might either reflect the Republicans' desire to make themselves comparable to the ruling party.

Looking at Twitter users exclusively, we find that users have less incentive to delay adoption if a large number of their peers have already adopted, where we define peers based on two definitions of a social network between politicians: the first being a network between representatives belonging to the same committees, and the second being a network between representatives of different districts within the same state. As a robustness check, we verify that the peer effects hold even when exogenous network characteristics and correlated effects are controlled for. To explain our findings, we provide some evidence in favor of social learning, since the peer effect is strongest when representatives have had no experienced with Facebook and/or when representatives have been in office long enough to develop their state network. To address our concerns that our findings might be artificially generated by those who adopted Twitter simply because of some important event, like Barrack Obama's inauguration, we redo the estimations using sub-samples that discard representatives who began using Twitter around the time of January 20, 2009. The peer effects do not disappear, but instead, become larger in magnitude (while maintaining significance) after our sub-sample adjustments. Finally, we show using *ex post* Twitter usage statistics, that unobserved heterogeneity is unlikely to drive our results.

Social learning is becoming an increasingly important area of research in empirical microeconomics. Moreover, as politicians from other countries, such as Canada and the United Kingdom[29] are also beginning to adopt Twitter, the topic on social media and politics has never been more relevant. Motivated by trends in both popular culture and academia, our research provides a better understanding about how communication technology actually diffuses, representative to representative, which is made possible by our detailed information about each representative's precise time of adoption. This paper fills the void in research on Twitter and politics by establishing the incentives behind the adoption decision, while this paper serves as a simple example of how the concept of delay can be identified using data. The next section illustrates that this paper should motivate subsequent economics research about social media and politics.

[29] High ranking politicians from both countries are known to use Twitter as well.

5.2 Future research agenda

Although the paper has helped us understand the diffusion mechanism for Twitter, much is still unknown about the real impact of Twitter and social media. The danger of decentralizing media is that information may no longer be as reliable. With the abundance of Internet content, the time it takes to evaluate all this content may drain society of its productivity. Does the promise of (short term) attention actually provide enough incentive for Twitter personalities to publish Tweets that are informative and helpful to followers? Finding out about mundane details of a politician's daily chores may simply be a waste of time for readers. Furthermore, the politicians may discover over time that Twitter's value has been overrated. To move research about Twitter into a normative direction, we discuss three possible extensions to our current paper.

5.2.1 Political impact of Twitter adoption

The most obvious extension of our paper would be to look at the impact that Twitter adoption has on election outcomes. Since the majority of Twitter adoption occurred after the 2008 election, but before 2010, future research should be able to identify the treatment affect associated with Twitter. This way, we will better understand whether constituents are actually buying into the marketed benefits of social media. Do voters actually care about transparent government? Moreover, do they believe that Twitter actually makes government more transparent?

5.2.2 Financial impact of Twitter adoption

Financial markets are hungry for whatever information they can find. A combination of uninhibited[30] Twitter posts paired with technological advances in Twitter statistical analysis, future research in the near term should be able to identify whether Twitter can help provide information to investors. For example, are Twitter posts of those belonging to the Financial Services Committee informative? More specifically, can their Twitter posts predict future policies that affect the financial industry. We can further generalize this idea to Twitter posts of firms and whether they affect abnormal returns.

[30] For example, politicians visiting Iraq have not used enough discretion in what they posted on Twitter, as stated in the news article by Michael Falcone (2009): In Iraq: To Twitter or Not to Twitter? The New York Times, February 9, 2009.

5.2.3 Longevity of Twitter adoption

There is no guarantee that social learning can actually lead to more accurate information regarding merits of Twitter, as people in general can always learn the "wrong" state of the world[31]. The politicians, however, can learn correctly *ex post* whether Twitter is actually a useful communications technology. This means that one can collect data on the exit from Twitter to identify whether politicians (felt) they made the right decision about Twitter or not. We believe that *ex post* data on how long Twitter adopters stay with Twitter will be informative in this respect.

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6 Appendix

6.1 Non-algebraic intuition behind prediction

We turn to Chamley and Gale's (1994) model to justify why it an increase in the number of peer adopters can accelerate own adoption. In their model of investment delay, there are a finite number of agents who must decide when to adopt. Their timing decisions are based on threshold conditions on the beliefs about the investment; in our case, the belief would be some posterior probability about whether Twitter adoption is good. Adopting in the current period will yield a perceived benefit, based on the most updated beliefs net some adoption cost. Beliefs are updated in a Bayesian manner, and depend on the past investment decisions of others. Alternatively, waiting until the next period will give an agent some option value associated with delay, which is essentially the value associated with "reversing a decision" upon conditioning on the subsequent period's updated information.

The trade-off between the option value and opportunity cost of delay creates an arbitrage condition for which equilibrium is based on. Adoption will thus be defined by the equilibrium belief thresholds balance this trade-off. In their model, both the option value and opportunity cost depend on the equilibrium beliefs; however, only the option value depends on the number of potential adopters who have yet to adopt. This means that as more peers within a social network (of fixed size) adopt, the number of potential adopters to draw information from in the future decreases commensurately. Therefore, the option value decreases as adoption among peers increases, all else held fixed. For the arbitrage condition to hold, the equilibrium beliefs must be adjusted so as to reduce the opportunity cost of delay (i.e. benefit of adoption). Clearly, the benefit of adoption increases with a representative's belief regarding its merit; that said, the opportunity cost of delay has to be adjusted downward by reducing the equilibrium beliefs. But since the equilibrium beliefs correspond to the threshold condition, the probability of forming a new belief that exceeds this threshold will increase, ultimately, increasing the likelihood of adoption.

With respect to our data, this means that conditional on everything else, politicians should adopt Twitter sooner if a large number of peers have already done so.

6.2 Detailed data description

A list of the variables and short descriptions for each are provided below:

1. The variables log(Population), log(Income) and the percentage of black residents are based on the population numbers from the 2000 U.S. Census (as this study was conducted before the 2010 Census).

2. Personal information about each candidate, such as gender, race, education, age, tenure, party affiliation, profession and religion were collected using a combination of the directory of representatives, their personal websites, and Wikipedia. Information common to all sources were cross referenced with one another to ensure that the accuracy of our information was not dependent on the source. The information about education and past occupation are based on the representative's most recent degree and professions. We categorize education and profession using two dummy variables, a dummy that indicates whether the representative went to an Ivy League school, and another dummy that indicates whether the representative was an attorney, judge or lawyer. Furthermore, we categorize religion using a dummy indicating

whether a candidate is Catholic or not. A representative's tenure is based on the number of years he/she has been in office as a representative in the House of Representatives. We do not count past experience in state level politics towards our measure of tenure.

3. MySpace, RSS, Flickr, Facebook, and/or Youtube use are indicated on each representative's personal homepage. Because of the amount of identity theft in social media, we do not indicate that a representative adopted a particular technology, unless it is explicitly stated on their website; even if an Internet search produces a Facebook link to that representative. On the other hand, we are able to use both the representative's endorsement within a homepage as well as Internet searches to identify Twitter use because of Twitter's "verified" feature, which ensures that the online persona corresponds to its true corresponding identity. The date of the first Twitter post was collected by going to each user's first page of posts and recording the date of the earliest one.

4. Voting data from 2008 was collected from http://clerk.house.gov/. The variable party votes corresponds to the percentage of votes in favor of the presidential candidate corresponding to the representative's party loyalties. The percentage of votes in favor of the representative himself/herself is captured by the variable representative votes.

5. Each representative belongs to as few as 0 and as many as 4 committees. We identify which committees each representative belongs to by going to each committee's website and looking up its membership. The committees that we consider are the committees on agriculture, appropriations, armed service, budget, education, energy, financial services, foreign relations, homeland security, house administration, economic, taxation, judiciary, natural resources, oversight, intelligence, rules, science and technology, small business, official conduct, transportation and infrastructure, and ways and means.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
log(Population)	13.364	0.214	10.96	15.2	438
log(Income)	10.643	0.262	9.620	11.43	438
Percentage black	12.637	15.963	0	96.400	438
Gender	0.167	0.373	0	1	438
Black	0.082	0.275	0	1	438
Catholic	0.292	0.455	0	1	438
Law	0.352	0.478	0	1	438
Ivy	0.098	0.298	0	1	438
Age	57.333	10.16	28	86	438
Incumbent	0.861	0.347	0	1	438
Tenure	9.550	8.711	0	54	438
Democrat	0.598	0.491	0	1	438
Party votes	0.516	0.1	0	0.963	432
Representative votes	0.656	0.124	0.268	1	427
Number of committees	1.936	0.826	0	4	438
MySpace	0.014	0.116	0	1	438
RSS	0.573	0.495	0	1	438
Flickr	0.151	0.358	0	1	438
Facebook	0.571	0.496	0	1	438
Youtube	0.731	0.444	0	1	438
Adoption in state network	5.849	6.104	0	22	438
Adoption in committee network	28.902	18.506	0	78	438

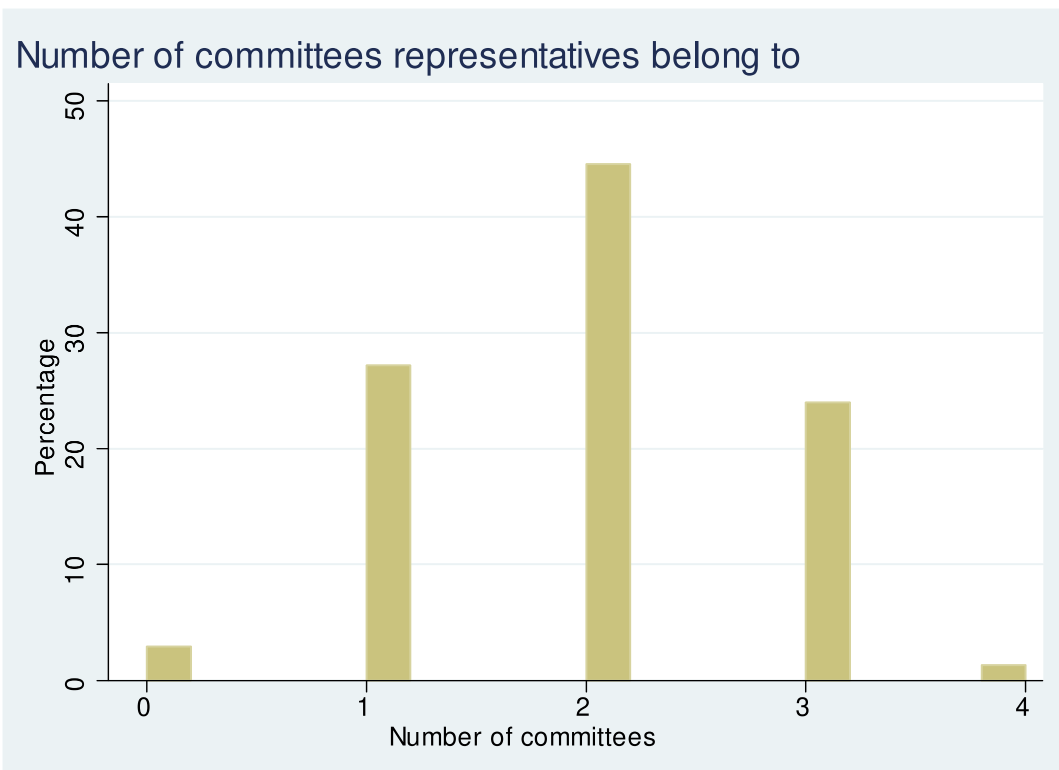


Table 2: Propensity to adopt Twitter

	(1)		(2)		(3)	
	Adopt		Adopt		Adopt	
log(Population)	0.904*	(0.379)	0.866*	(0.360)	-0.337	(1.557)
log(Income)	0.190	(0.285)	0.194	(0.291)	0.327	(0.320)
Percentage black	0.00410	(0.00544)	0.00460	(0.00549)	0.00324	(0.00559)
Gender	0.263	(0.177)	0.303	(0.182)	0.244	(0.186)
Black	-0.229	(0.315)	-0.280	(0.325)	-0.383	(0.327)
Catholic	0.0901	(0.157)	0.102	(0.158)	0.0441	(0.166)
Law	0.0394	(0.142)	0.0505	(0.143)	0.00542	(0.153)
Ivy	0.330	(0.226)	0.362	(0.233)	0.306	(0.240)
Age	-0.00995	(0.00792)	-0.0269*	(0.0127)	-0.00625	(0.00838)
Incumbent	-0.302	(0.213)	-0.258	(0.224)	-0.495*	(0.232)
Tenure	-0.00624	(0.0108)	-0.0231	(0.0462)	-0.0101	(0.0115)
Democrat	-0.802***	(0.154)	-1.026***	(0.238)	-0.787***	(0.171)
Number of committees	-0.0177	(0.0868)	-0.0166	(0.0875)	-0.0192	(0.0902)
MySpace	0.785	(0.729)	0.742	(0.693)	1.050	(0.744)
RSS	0.234	(0.141)	0.226	(0.143)	0.233	(0.151)
Flickr	0.400*	(0.185)	0.385*	(0.185)	0.317	(0.199)
Facebook	0.691***	(0.151)	-0.778	(0.773)	0.763***	(0.163)
Youtube	0.158	(0.175)	0.189	(0.178)	0.139	(0.188)
Facebook * Tenure			0.000253	(0.000692)		
Facebook * Age			0.0223	(0.0134)		
Facebook * Democrat			0.348	(0.282)		
Party votes					-0.0749	(0.774)
Representative votes					1.736*	(0.675)
Constant	-13.83*	(5.762)	-12.34*	(5.652)	0.120	(20.97)
Observations	438		438		396	
McFadden R^2	0.189		0.197		0.189	
BIC	598.1		612.1		551.8	

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 3: Speed of adoption: main results

	(1) Days to adopt		(2) Days to adopt		(3) Days to adopt	
log(Population)	-33.45	(22.90)	-32.22	(22.71)	-43.06	(29.53)
log(Income)	2.140	(4.637)	1.383	(4.282)	0.941	(5.491)
Percentage black	-0.0704	(0.0747)	-0.0860	(0.0798)	-0.0909	(0.0871)
Gender	-2.662	(1.689)	-2.682	(1.717)	-2.320	(2.177)
Black	-0.300	(3.551)	0.495	(3.995)	-0.688	(3.830)
Catholic	-1.669	(1.817)	-0.978	(1.641)	-0.957	(1.520)
Law	-0.446	(1.656)	-0.390	(1.819)	-1.278	(2.476)
Ivy	-3.026	(1.841)	-2.930	(1.726)	-2.931	(2.556)
Age	-0.0348	(0.0806)	-0.0334	(0.0852)	-0.0928	(0.102)
Incumbent	-0.608	(1.972)	-1.175	(2.033)	0.154	(2.736)
Tenure	0.0594	(0.121)	0.0906	(0.125)	0.158	(0.127)
Democrat	2.109	(1.672)	2.358	(1.606)	2.350	(1.828)
Party votes	7.464	(9.688)	8.109	(9.104)	6.080	(10.81)
Representative votes	-0.422	(6.476)	0.279	(6.534)	0.587	(7.192)
Number of committees	-0.365	(0.979)	-4.187*	(1.739)	6.818	(5.233)
MySpace	-4.409*	(2.110)	-3.861	(2.336)	-3.898	(3.250)
RSS	1.648	(2.102)	2.180	(2.311)	2.245	(3.176)
Flickr	1.553	(1.747)	1.412	(1.707)	1.705	(1.998)
Facebook	-2.818	(2.423)	-2.619	(2.432)	-3.445	(3.220)
Youtube	-3.772	(3.879)	-3.368	(3.783)	-2.512	(3.384)
Adoption in state network	0.139	(0.166)	0.420	(0.324)	0.415	(0.363)
Adoption in committee network	-0.161*	(0.0699)	-0.265*	(0.102)	-0.253*	(0.117)
Democrats in state network			-0.0647	(0.141)	-0.108	(0.167)
Democrats in committee network			0.194*	(0.0774)	-0.267	(0.200)
Constant	437.6	(342.7)	426.2	(338.0)	579.2	(440.4)
Committee controls	No		No		Yes	
Observations	180		180		180	
R^2	0.1473		0.1776		0.2563	

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4: Speed of adoption: robustness checks

	(1)		(2)	
	Days to adopt		Days to adopt	
log(Population)	-45.52	(29.59)	-42.33	(28.86)
log(Income)	0.0449	(5.528)	0.874	(5.449)
Percentage black	-0.104	(0.0867)	-0.0902	(0.0817)
Gender	-2.142	(2.171)	-2.330	(2.236)
Black	-0.324	(3.685)	-2.658	(3.328)
Catholic	-0.215	(1.611)	-0.530	(1.811)
Law	-1.297	(2.435)	-0.792	(2.351)
Ivy	-3.465	(2.453)	-3.600	(2.629)
Age	-0.0973	(0.100)	-0.108	(0.102)
Incumbent	-0.255	(2.619)	-0.477	(2.760)
Tenure	0.172	(0.121)	0.184	(0.117)
Democrat	2.370	(1.751)	2.042	(1.916)
Party votes	4.968	(10.61)	4.410	(12.10)
Representative votes	0.550	(7.218)	6.060	(6.593)
Number of committees	3.962	(5.419)	6.474	(5.343)
MySpace	-4.528	(3.529)	-3.351	(3.300)
RSS	2.438	(3.192)	1.889	(3.036)
Flickr	1.624	(1.981)	1.414	(2.047)
Facebook	-3.263	(3.200)	-2.489	(2.903)
Youtube	-3.302	(3.377)	-3.377	(3.595)
Adoption in state network	0.415	(0.365)		
Adoption in committee network	-0.341**	(0.126)		
Democrats in state network	-0.0882	(0.162)	0.00500	(0.107)
Democrats in committee network	-0.145	(0.214)	-0.305	(0.197)
Month-year time dummy	0.256*	(0.107)	0.213	(0.116)
Percentage adoption in state network			-4.915	(7.372)
Percentage adoption in committee network			-19.16	(9.983)
Constant	619.3	(441.8)	569.0	(430.7)
Committee controls	Yes		Yes	
Observations	180		180	
R^2	0.2783		0.2611	

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5: Speed of adoption: by party specific peer effects

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
log(Population)	-31.86	(22.70)	-31.03	(23.01)	-31.78	(22.78)
log(Income)	1.525	(4.273)	2.137	(4.493)	1.481	(4.259)
Percentage black	-0.0783	(0.0774)	-0.0726	(0.0776)	-0.0814	(0.0790)
Gender	-3.084	(1.657)	-2.461	(1.651)	-2.695	(1.615)
Black	0.0303	(3.647)	-0.280	(3.819)	0.612	(3.728)
Catholic	-0.959	(1.677)	-0.993	(1.684)	-0.763	(1.675)
Law	0.435	(1.807)	-0.657	(1.688)	0.257	(1.735)
Ivy	-3.044	(1.752)	-2.914	(1.888)	-3.040	(1.702)
Age	-0.0634	(0.0849)	-0.0788	(0.0875)	-0.0761	(0.0888)
Incumbent	-0.670	(2.023)	-0.771	(1.991)	-0.885	(2.019)
Tenure	0.0970	(0.119)	0.103	(0.128)	0.138	(0.126)
Democrat	0.680	(1.674)	2.786	(2.288)	2.350	(2.174)
Party votes	8.623	(8.863)	4.933	(9.979)	5.906	(8.320)
Representative votes	2.935	(6.311)	-0.525	(6.390)	1.956	(6.468)
Number of committees	-3.971*	(1.623)	-3.815*	(1.748)	-4.160*	(1.672)
MySpace	-5.101*	(2.265)	-2.672	(1.842)	-5.356*	(2.153)
RSS	1.179	(2.257)	1.911	(2.282)	1.036	(2.313)
Flickr	1.807	(1.686)	2.367	(1.743)	2.072	(1.669)
Facebook	-2.186	(2.273)	-2.741	(2.477)	-1.964	(2.227)
Youtube	-2.702	(3.979)	-3.937	(4.092)	-2.897	(4.115)
Democrats in state network	0.0438	(0.0855)	-0.0556	(0.121)	-0.00358	(0.115)
Democrats in committee network	0.179*	(0.0718)	0.0824	(0.0562)	0.195**	(0.0732)
Adoption in state network (D)			-0.0550	(0.613)	-0.403	(0.602)
Adoption in state network (R)			0.567	(0.679)	0.733	(0.604)
Adoption in committee network (D)	0.460*	(0.204)			0.471*	(0.216)
Adoption in committee network (R)	-0.614***	(0.153)			-0.640***	(0.169)
Constant	419.5	(338.6)	407.2	(342.2)	420.0	(340.0)
Observations	180		180		180	
R^2	0.1959		0.1391		0.2127	

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 6: Speed of adoption: evidence of social learning

	(1) Days to adopt		(2) Days to adopt	
log(Population)	-33.30	(21.68)	-33.66	(22.77)
log(Income)	3.670	(4.229)	2.340	(4.780)
Percentage black	-0.0711	(0.0750)	-0.0638	(0.0740)
Gender	-3.013	(1.755)	-2.586	(1.697)
Black	-0.132	(3.519)	-0.395	(3.839)
Catholic	-2.591	(2.018)	-1.990	(1.864)
Law	-0.730	(1.616)	-0.591	(1.718)
Ivy	-2.362	(1.852)	-3.132	(1.839)
Age	0.00251	(0.0908)	-0.0406	(0.0805)
Incumbent	-0.371	(1.872)	-0.530	(1.966)
Tenure	-0.0154	(0.116)	0.291	(0.255)
Democrat	2.364	(1.670)	2.073	(1.664)
Party votes	5.852	(9.843)	5.695	(10.17)
Republican votes	3.217	(6.474)	-0.560	(6.619)
Number of committees	-0.611	(1.012)	-0.115	(0.995)
MySpace	-3.258	(2.090)	-5.355*	(2.636)
RSS	1.362	(1.934)	1.554	(2.075)
Flickr	2.275	(1.799)	1.359	(1.767)
Facebook	-10.36	(5.605)	-2.380	(2.356)
Youtube	-3.594	(3.718)	-3.724	(3.849)
Adoption in state network	0.152	(0.173)	0.294	(0.226)
Adoption in committee network	-0.0673	(0.0666)	-0.111	(0.0801)
Non-Facebook * Adoption in state network	-0.686	(0.729)		
Non-Facebook * Adoption in committee network	-0.348	(0.192)		
Tenure * Adoption in state network			-0.0162	(0.0160)
Tenure * Adoption in committee network			-0.00822	(0.00780)
Constant	422.4	(318.4)	437.4	(340.9)
Observations	180		180	
R^2	0.2006		0.1600	

Standard errors in parentheses

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 7: Speed of adoption: sensitivity to inauguration date

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
log(Population)	-35.52*	(16.80)	-69.99**	(25.14)	-90.90**	(29.70)
log(Income)	2.546	(4.350)	0.639	(5.277)	-0.320	(6.442)
Percentage black	-0.115	(0.0972)	-0.210	(0.119)	-0.293*	(0.144)
Gender	-3.068	(2.887)	-2.652	(3.616)	-5.654	(4.173)
Black	1.668	(6.480)	5.069	(8.445)	6.631	(9.801)
Catholic	-1.592	(2.245)	-2.629	(2.553)	-6.148	(3.265)
Law	-1.195	(2.032)	-1.316	(2.400)	1.144	(3.244)
Ivy	-4.074	(3.420)	-5.927	(4.084)	-9.351	(5.605)
Age	-0.109	(0.118)	-0.135	(0.141)	-0.164	(0.187)
Incumbent	-1.852	(2.944)	-2.522	(3.646)	-2.371	(5.105)
Tenure	0.123	(0.151)	0.137	(0.176)	0.0545	(0.219)
Democrat	1.452	(2.224)	2.280	(2.559)	3.705	(3.392)
Party votes	7.515	(10.31)	10.05	(13.52)	25.54	(16.41)
Representative votes	2.315	(9.506)	0.328	(11.26)	-6.787	(13.80)
Number of committees	-5.158*	(2.255)	-5.573	(2.903)	-7.069	(3.644)
MySpace	-4.805	(6.424)	-1.614	(9.635)	0.266	(10.63)
RSS	2.502	(2.144)	3.500	(2.545)	3.083	(3.339)
Flickr	2.118	(2.443)	0.855	(2.870)	-0.893	(3.719)
Facebook	-3.013	(2.383)	-3.788	(2.700)	-3.685	(3.357)
Youtube	-4.164	(2.928)	-3.023	(3.248)	-4.854	(4.008)
Adoption in state network	0.230	(0.363)	0.137	(0.408)	-0.0282	(0.493)
Adoption in committee network	-0.274**	(0.0961)	-0.329**	(0.107)	-0.368**	(0.122)
Democrats in state network	0.0202	(0.150)	0.0851	(0.177)	0.159	(0.223)
Democrats in committee network	0.207*	(0.0918)	0.240*	(0.113)	0.271	(0.142)
Constant	465.8*	(228.2)	950.1**	(344.8)	1246.3**	(406.9)
Observations	151		126		94	
R^2	0.2410		0.2951		0.3954	

Standard errors in parentheses

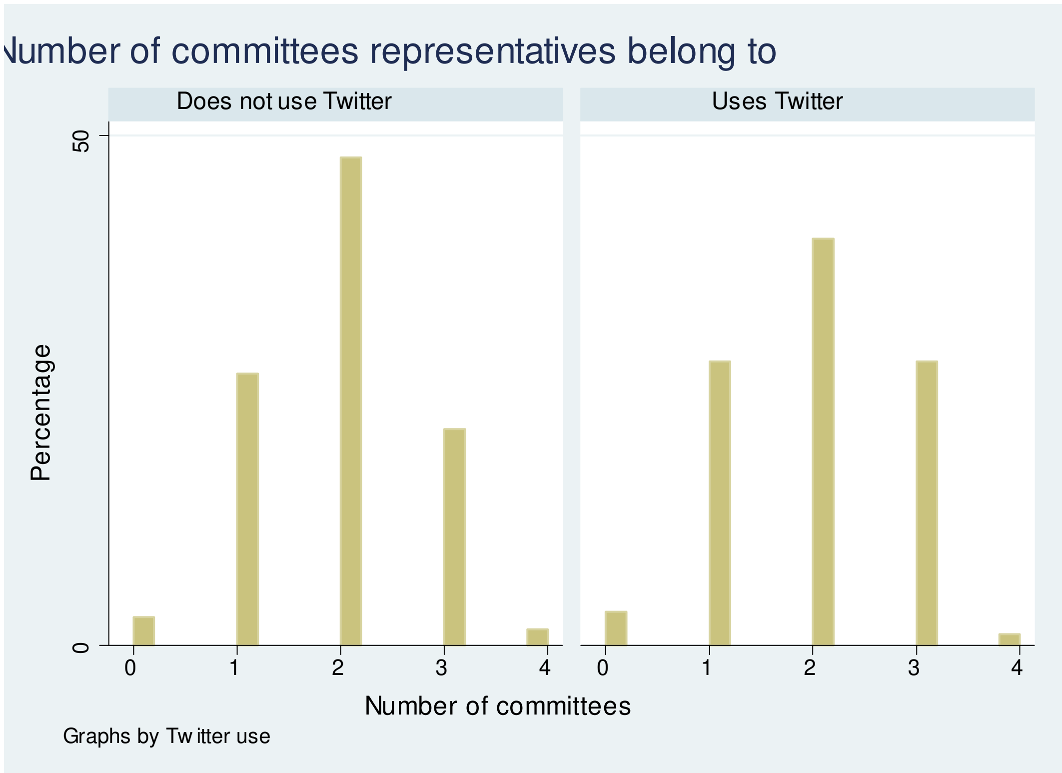
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

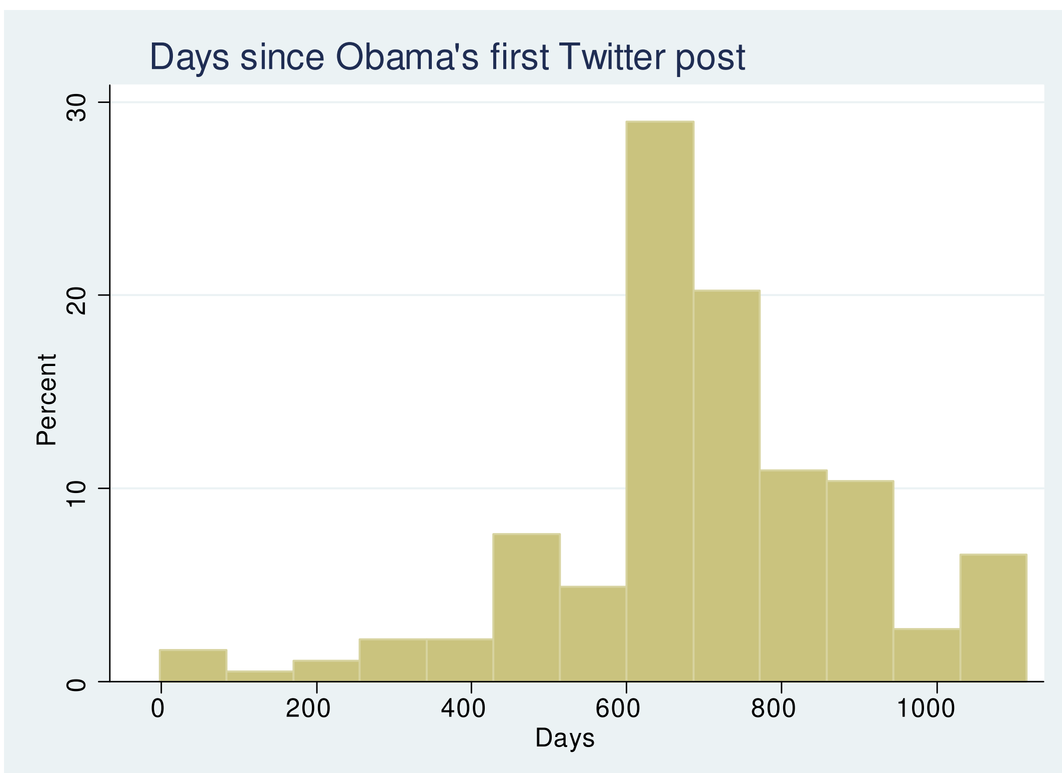
Table 8: Ex post Twitter usage and adoption speed

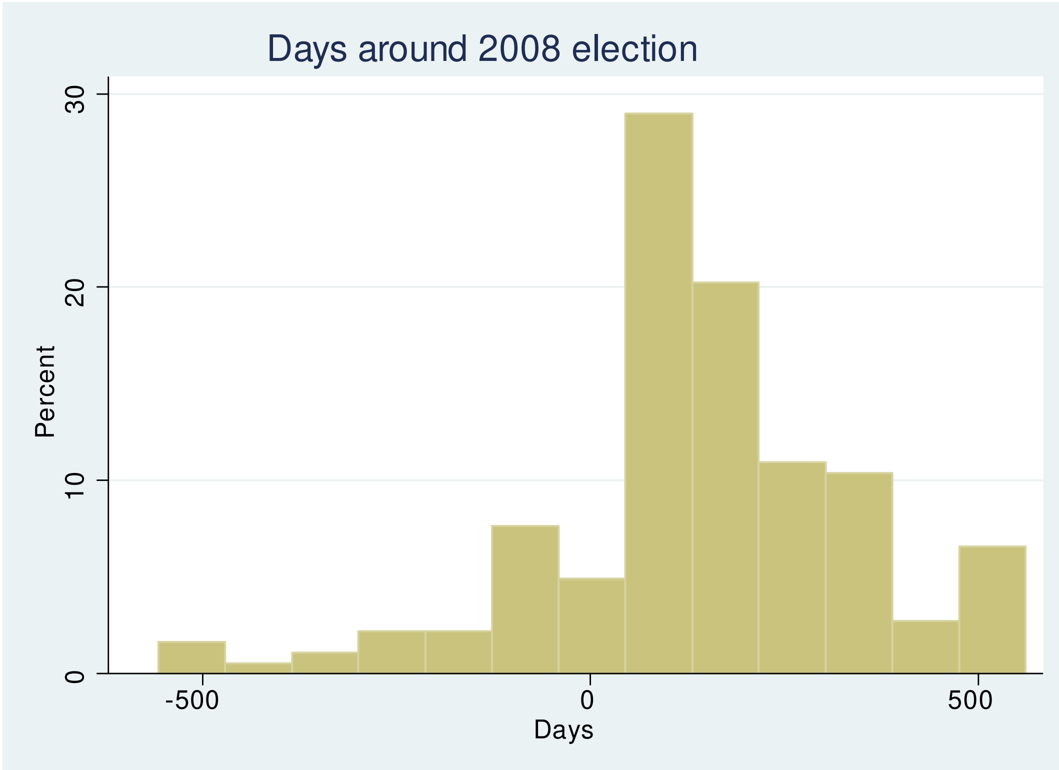
	(1)		(2)		(3)	
	Tweets per day		Followers per day		Following per day	
Days to adopt	-0.000551	(0.00502)	0.0349	(0.0406)	0.0132	(0.0268)
Constant	0.766***	(0.0623)	5.433***	(0.503)	1.867***	(0.332)
Observations	182		182		182	
R^2	0.0001		0.0041		0.0014	

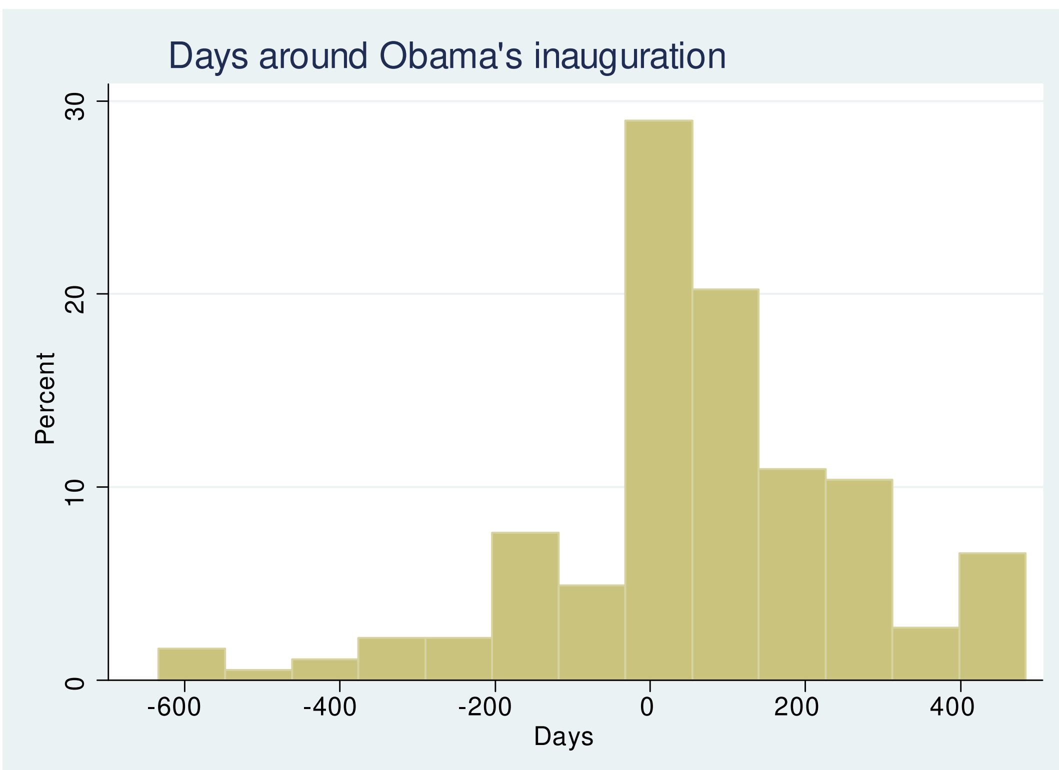
Standard errors in parentheses

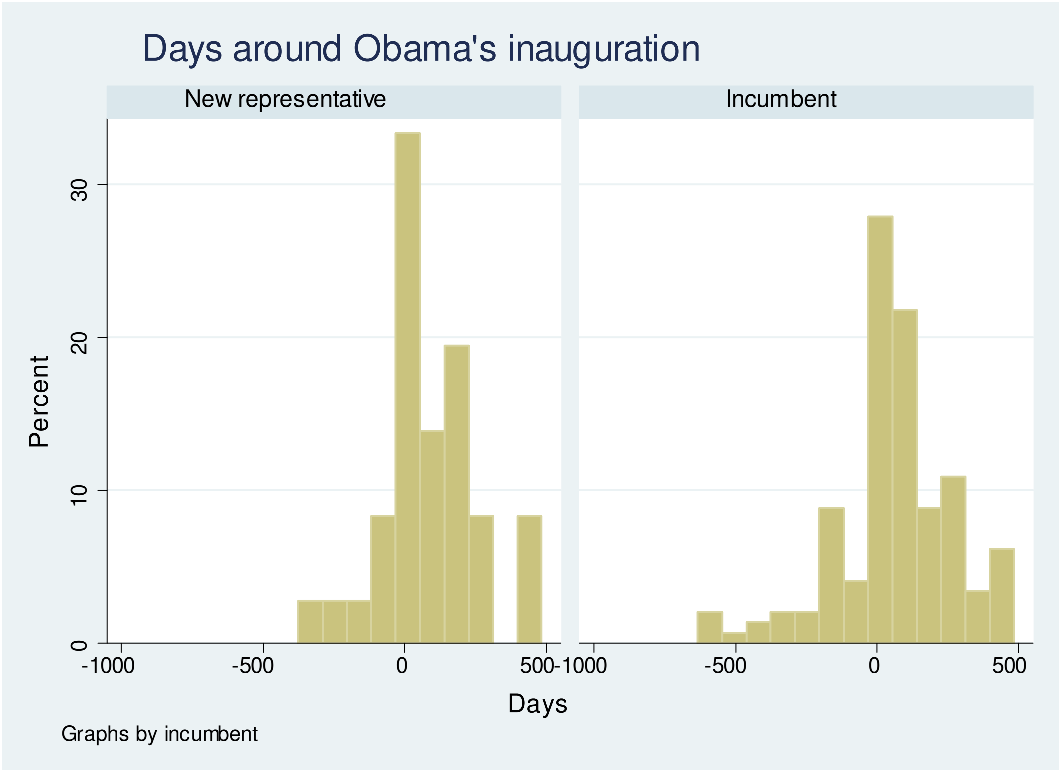
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

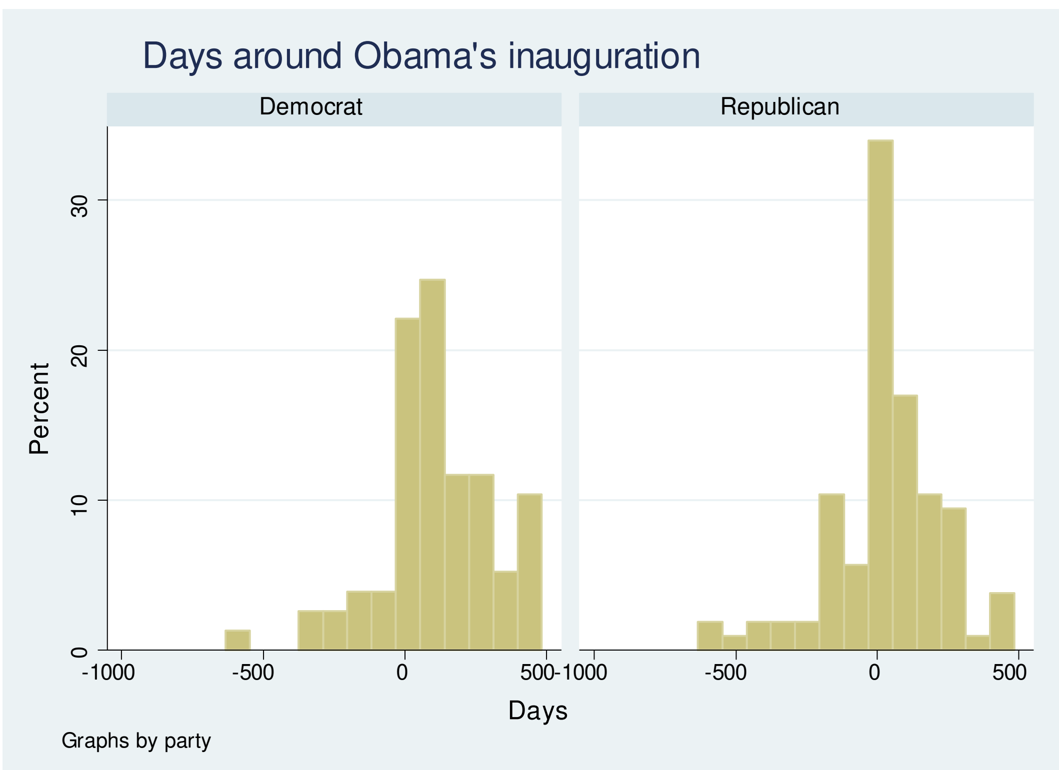

Number of committees representatives belong to
Does not use Twitter
Uses Twitter
Percentage
50
0
0
1
2
3
4
0
1
2
3
4
Number of committees
Graphs by Tw itter use

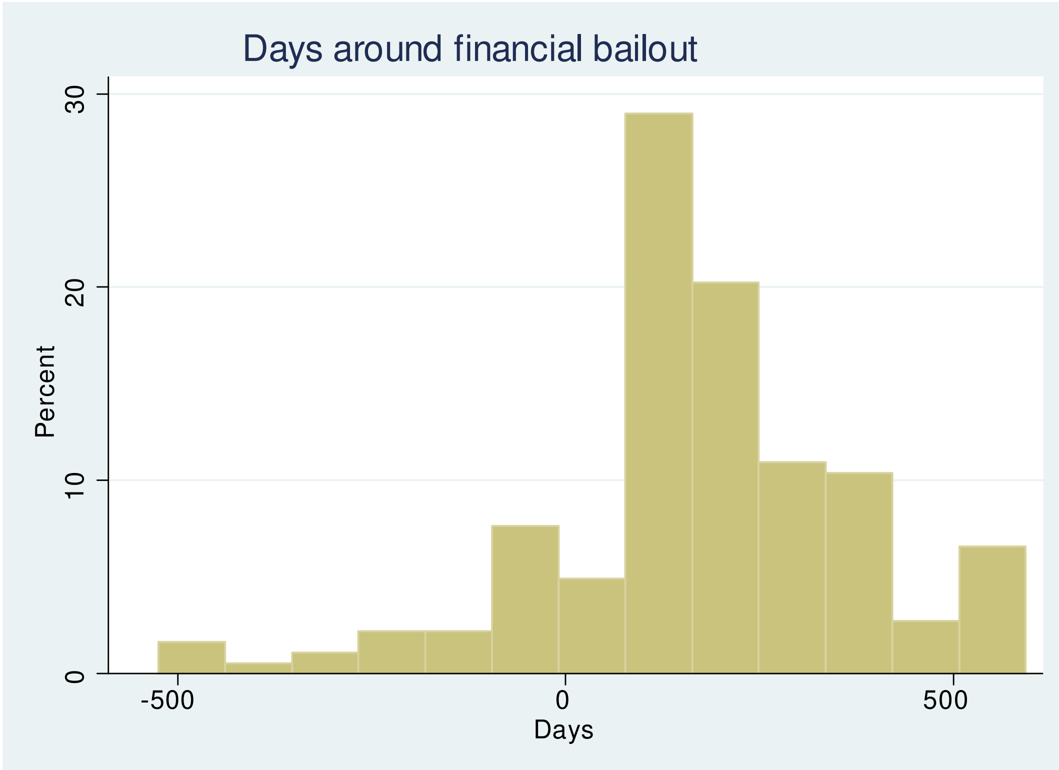

Days since Obama's first Twitter post
Percent
30
20
10
0
0
200
400
600
800
1000
Days

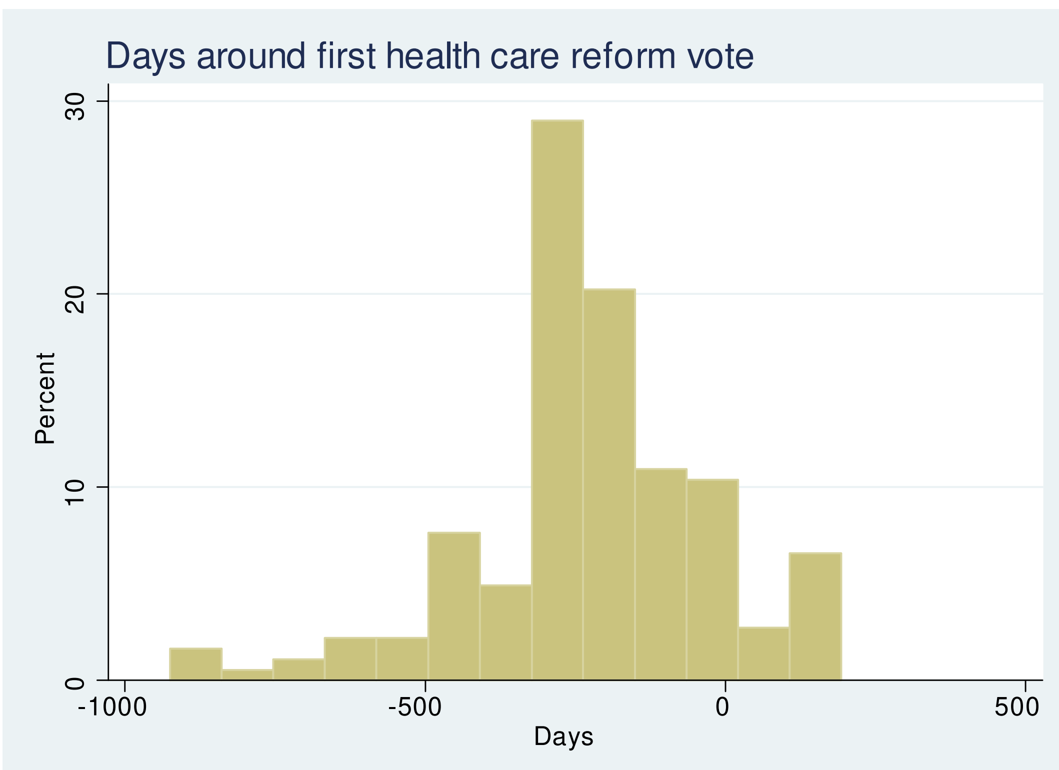

Days around 2008 election
Percent
0
10
20
30
-500
0
500
Days

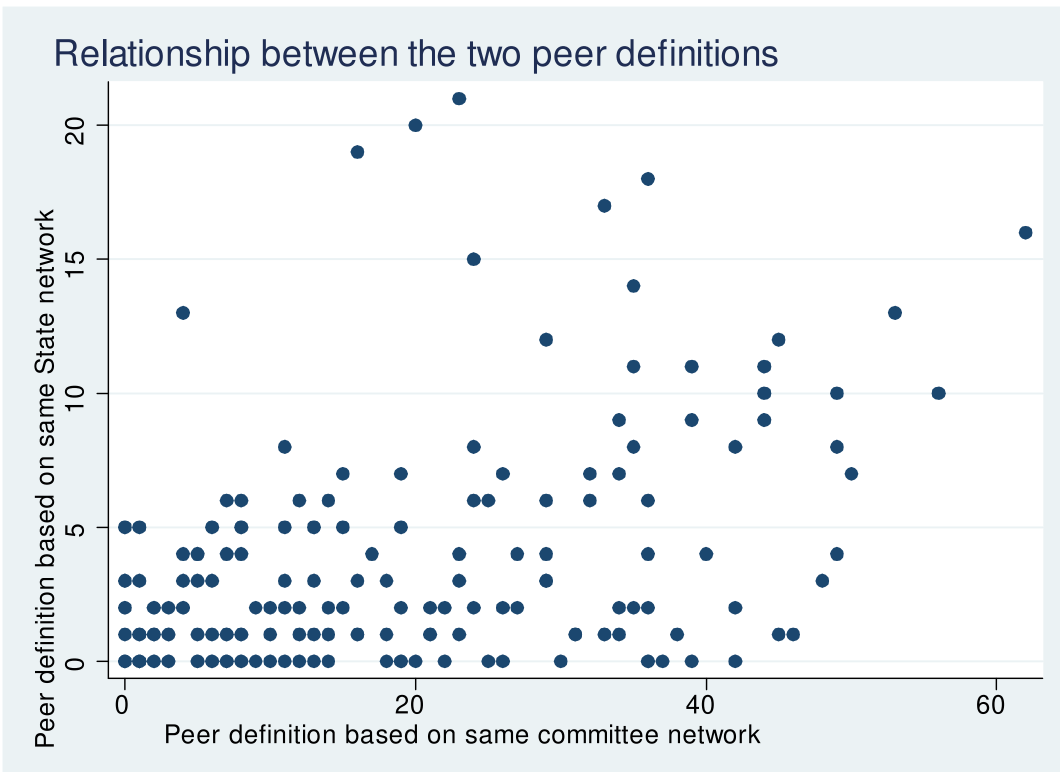

Days around Obama's inauguration
Percent
0
10
20
30
-600
-400
-200
0
200
400
Days


Days around Obama's inauguration
New representative
Incumbent
Percent
0
10
20
30
-1000
-500
0
500
Days
Graphs by incumbent


Days around Obama's inauguration
Democrat
Republican
Percent
0
10
20
30
-1000
-500
0
500
Days
Graphs by party


Days around financial bailout
Percent
0
10
20
30
-500
0
500
Days


Days around first health care reform vote
Percent
0
10
20
30
-1000
-500
0
500
Days


Relationship between the two peer definitions
Peer definition based on same State network
Peer definition based on same committee network
0
5
10
15
20
0
20
40
60