Twitter Adoption in Congress

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Abstract

We study the early adoption of Twitter in the 111th House of Representatives. Our main objective is to determine whether successes of past adopters have the tendency to speed up Twitter adoption, where past success is defined as the average followers per Tweet - a common measure of "Twitter success" - among all prior adopters. The data suggests that accelerated adoption can be associated with favorable past outcomes: increasing the average number of followers per Tweet among past adopters by a standard deviation (of 8 followers per Tweet) accelerates the adoption time by about 112 days. This acceleration effect is weaker for those who already have adopted Facebook and those who have access to information about a large number of past adopters. We later find a positive relationship between an adopter's realized followers per Tweet and the success of adopters preceding him/her. Thus, there may exist benefits associated with adopting Twitter based on past successes of others. In general, the patterns we find are consistent with predictions generated by a simple model of adoption delay with learning.

Keywords: Diffusion of technology, network effects, political marketing, social learning, social media.

JEL: M3, D83, D85.

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1 Introduction

Social learning can occur under two general contexts. Agents within a community can learn from one another through past actions or outcomes of their peers. While economic theory gives us a rich set of predictions for both contexts, the general body of empirical literature has primarily focused on identifying these peer effects under the context of social learning through observed actions; despite the fact that clean identification of these effects associated with peer behavior is inherently hard (if not impossible). For one thing, these so-called peer effects may be spurious; and even if they are not spurious, they are not necessarily caused by learning, as competing explanations involving crowding and network externalities often play a (larger) role. Using information about past outcomes would certainly alleviate some of these identification problems. We conjecture that this void in the literature is likely due to the fact that obtaining data on both agent behavior and their relevant outcomes is hard to come by. That said, this paper proposes using data from the recent Twitter adoption craze among American Congressional members to address some of these deficiencies in current research.

Our data about Twitter adoption in the 111th House of Representatives is interesting for two reasons: 1) we can observe the precise day in which a representative made his/her first Twitter post (i.e., the date of adoption); and 2) their realized and publicly observable success at attaining followers per Twitter post (i.e., a typical metric for influence on Twitter[1]). The order of each politician's adoption allows us to measure the potential amount of information available to them at the time of adoption; that is, for each adopter, we can approximate the success of his/her predecessors he/she can potentially observe. Therefore, we can estimate the link between positive information - in the form of large averages for the followers/Tweet among past adopters - and the date of adoption for a politician in question that may exist. Given the novelty of Twitter in general, we expect that these information signals generated by past adoption behavior to play some role in the decisions of potential adopters. Even though the monetary cost of opening a Twitter account is zero, politicians may still be hesitant to adopt Twitter right away if doing so yields lackluster follower/Tweet statistics, thereby revealing their weak support. However, if they observe that other politicians have been successful at maintaining a follower base, then adopting soon after may also generate these benefits.

We first establish a relationship between the incentive to adopt early and favorable signals using a simple model of delay. In the model, a risk averse agent has to decide whether to adopt a new

[1] Refer to Comm (2010) for more details.

technology of uncertain value today, or wait until tomorrow. By waiting until the next period, he enjoys the possibility of receiving an additional information signal (on top of the set already available to him). Because he discounts the future, this updated posterior comes at a price. In light of favorable signals, the incentive to adopt right away increases: any value that comes from an additional signal next period will be outweighed by the opportunity cost of missing out on a high expected payoff (based on less information). The model also predicts that the agent will not wish to wait if his initial prior is already precise. Furthermore, the impact associated with favorable signals is dampened if the agent has already observed a large number of signals. In other words, these signals matter very little to those who are already knowledgeable. Our last observation from this model is that the impact associated with favorable signals is concave.

Interpreting the followers/Tweet outcomes among past adopters as information signals, we estimate the impact that these signals have on the number of days it takes a politician to adopt Twitter. Our baseline estimates reveal that a standard deviation increase in the average followers/Tweet among past adopters decreases the time of adoption by about 112 days. Furthermore, those who have already adopted Facebook begin using Twitter soon, are less influenced by increases in the average followers/Tweet based on past information. As Facebook and Twitter are very similar, one may argue that those with Facebook have a more precise prior about the merits of Twitter; thus, these patterns are consistent with what our simple model would predict. Similarly, we find that the acceleration effect associated with favorable information is also dampened by the number of past adopters. Those who already have, potentially, access to a large set of signals may not enjoy much option value in waiting for new signals.

Further analysis of our data reveals an interesting lag structure between a Twitter user's own success, and the success of those before him: increasing the average followers/Tweet among past adopters is associated with an increase in a current adopter's own followers/Tweet by a proportionate amount. In other words, a politician who adopts soon after successful Twitter adopters may enjoy success himself. This result suggests that these information signals can actually benefit Twitter users.

Our extensions show that recent information about past adoption outcomes has a greater impact on older information about past adoption outcomes; however, more information in general has a greater impact on behavior and own realized outcome. We also consider the possibility that politicians react not to the raw information available to them about past outcomes, but instead, compare these observed outcomes to some expectation. As such, we evaluate the impact that positive and negative surprises have on the speed of adoption. Not surprisingly, an increase in the proportion of positive surprises associated with past outcomes accelerates adoption, while an increase in the average number of negative surprises decelerates adoption. Finally, we are able to find that while politicians do not appear to react much different to information sources coming from within and outside their home state, only those whose adoption occurs after a sequence of successful outcomes within the same state actually benefit. One may then stipulate the existence of some informational advantage associated with geography.

Why should politicians even care about how many users follow them on Twitter? Users who follow a politician will continually be updated with that politician's newest micro-blog entry. Those who choose to follow a politician are most likely people who actually want to read and pay attention to his content. Therefore, a person who chooses to add a politician to his follower list essentially designates this politician as an opinion leader (Boynton, 2010). Being an opinion leader may help a politician push controversial policies or satisfy his need for narcissistic self promotion (McFedries, 2007). In general, Twitter itself also cares about how many followers its users have. An important and efficient way to catalyze user generated content within a social network is to increase the number of captive followers/friends/readers each user has. Recent studies have shown that content generation largely depends on the size of a user's group of friends (Hofstetter, Shriver, and Nair, 2010; Zhang and Zhu, 2010). Twitter's role is to stimulate group formation, and what it gets in return is free content from its users. Not surprisingly, many social media outlets now push friendship/follower recommendations.

There are a number of confounding factors that can potentially discount our results. The first issue has to do with unobserved heterogeneity, or permanent correlated effects among adopters around similar time periods using Manski's (1993) terminology. While our data lacks the necessary panel structure for fixed effects estimation, we argue that under some assumptions, controlling for the order of entry may control for omitted variables such as unobserved adoption costs. The second issue has to do with sample selection, in that the adoption times we observe are only for those who adopted. We also acknowledge that some of the adoption decisions may have been made deterministically around the time of the start of office (January 20, 2009), or that information signals received by the earliest adopters are based on too few observations. Given that each politician makes his/her adoption decision in sequence, a relevant concern is temporal correlation of error terms across adopters around similar time intervals. This issue can be framed under Manski's setting as a transitory correlated effect, in that early adopters are likely to face similar time-sensitive shocks as their peers. Finally, contextual effects may also mislead us about the impact of past information. For instance, powerful politicians are likely to have a strong following on Twitter. Those who adopted soon after may not be doing so to exploit information externalities, but instead, making a desperate attempt to reach out to their peers with clout.

Our estimates appear to be robust to many of these problems, though, the magnitude of the acceleration effect associated with favorable past information drops considerably (but remains positive at a statistically significant level) when we control for autocorrelated errors. This caveat is likely the result from the fact that these decisions are often made days from one another. We view this limitation as a unique trade-off that our data presents: on the one hand, the sequential nature of observed behavior and outcomes allow us to circumvent a number of simultaneity problems associated with typical peer effects model, but on the other hand, this very sequential nature introduces temporal persistence of shocks that we are unable to control for (i.e., increasing media awareness about the effectiveness of Twitter as a self-promotion tool).

An alternative explanation for the patterns we observe is based on the idea of network externalities. If the average followers/Tweet proxies for potential interactions between politicians on Twitter, then the observed acceleration effect can be explained by some politicians wishing to wait until the online social network reaches some critical mass. Once they see that a large number of peers have already adopted, then Twitter is viewed as a valuable outlet to communicate with one another; note that under this alternative, politicians are not actually learning from one another. Unfortunately, we are unable to completely rule out the competing network effects story, as better data is needed. However, recent textual analysis by Golbeck, Grimes and Rogers (2010) hints that Twitter is primarily used as a 1-way broadcasting device as a means to spread information about them (for self promotion) and their forthcoming policies. One of their findings reveal that among the rare instances that 2-way communication actually takes place, these Tweets are 7 times more likely to be between non-politicians than fellow politicians. Therefore, our prior is that these network effects are unlikely to completely wash away the conjectured learning effects we find.

Aside from providing us a useful setting to study sequential learning, the use of Twitter in politics is itself an interesting and important topic. The desire to get all American politicians onto Twitter has led to organizations like TweetCongress.org, whose mandate is to encourage all politicians to adopt Twitter as a means to increase government transparency[2]. Although it is not obvious whether politicians are using Twitter for outreach or transparency (Chi and Yang, 2010;

[2] Similar organizations emerged in other countries, such as polTwitter.ca in Canada, and Tweetminster.co.uk in England.

Felten, 2009; Golbeck, Grimes, and Rogers, 2010), the role of Twitter represents a shift away from traditional government operations towards so-called E-Government. Perhaps the strongest motivation for E-Government is a recent study by Andersen (2009), which finds that the corruption index is typically lower for countries who employ E-Government practices. Not surprisingly, Twitter has marketed itself as being a useful tool for politicians to stay connected with their constituents and inform the public about their platforms/policies[3].

The paper is organized as follows. In Section 2, we outline recent and relevant literature that has guided this paper. Section 3 describes the unique data we hand-collected. We then proceed to describe a simple model of adoption delay in order to generate some predictions that can be tested with the data on hand. Our main empirical methodology is described in Section 5; included in that discussion is also a list of identification problems that we attempt to address. The main results are presented in Section 6. We then conclude with Section 7.

2 Related literature

Our work is most related to recent empirical work that aims to identify social learning. As mentioned earlier, there are two main approaches to identification of social learning[4]. The first is to infer learning based on the impact that peer behavior/perception has one's own behavior/perception. Some examples include the analysis of how average perceptions of HIV/AIDS risk within a social network affects one's own perception (Kohler, Behrman, and Watkins, 2007), the increased likelihood of purchasing a computer if a large proportion of neighbors have already done so (Goolsbee and Klenow, 2002), and how the adoption of new crops is affected by the adoption choices of farmers within a social network of friends and family (Bandiera and Rasul, 2006).

The second main approach, which is the one we incorporate, is to investigate whether past observable outcomes (affecting peers) has an impact on one's own behavior. Notable examples include the analysis of how box office surprises in opening weekend demand affect subsequent sales of movies (Moretti, 2010), whether the performance of schools that use new educational products/programs has an impact on the propensity that subsequent schools also adopt these products/programs (Forbes, 2009), and the impact of past farming outcomes within a social network affects a farmer's input decision (Conley and Udry, 2010). Our work complements the existing literature by offering a new perspective about sequential learning: instead of looking at how past

[3] Refer to Mashable's article "Twitter Goes to Washington, Hires Former Congressional Staffer" by Jolie O'Dell on November 4, 2010 (http://mashable.com/2010/11/04/twitter-washington/).

[4] Another approach is to incorporate structural econometric estimation, such as Buera, Monge-Naranjo, and Primiceri (2010) in their study of Bayesian learning among policy makers across countries.

outcomes affect the propensity to adopt, we investigate how past outcomes affect delay of adoption. By focusing on delay, we allow for the possibility of strategic learning. An agent may have an incentive to delay entry into Twitter so as to take full advantage these informational externalities bring.

Strategic learning is a heavily studied topic in economic theory. Perhaps the most relevant models are those proposed by Caplin and Leahy (1998), and Chamley and Gale (1994). Although the methods they use to study social learning are different, they both come to similar conclusions: the existence of information externalities may delay entry into uncertain environments. This incentive to "wait-and-see" has been used to explain a number of economic phenomena, such as slow recoveries after economic recessions, and investment lags into local/global markets.

In general, the empirical analysis of social learning is nested within the study of peer/network effects. Identifying peer effects is particularly challenging. As Manski (1993) points out, even if endogeneity and simultaneity of actions are addressed, the identification of peer effects are confounded by contextual and correlated group effects. Contextual effects refer to the fact that characteristics of a group may be driving the behavior of an agent in question, not the behavior of peers. Correlated effects refer to the fact that those in the same group may act in a similar manner for some unforeseen reason. In spite of these challenges, a number of interesting applications[5] have emerged, such as the study of peer effects under the context of school performance (Sacerdote, 2001), academic research (Waldinger, 2007), voting behavior among politicians (Cohen and Malloy, 2010), role of connections in institutional investing (Cohen, Frazzini and Malloy, 2009), and worker productivity (Mas and Moretti, 2009). A common way to address contextual effects is to include characteristics associated with the peers[6], as done in Markman et. al. (2003). To address correlated effects, one obvious approach would be to add group fixed effects, as done in Fletcher (2010). Contextual effects under the context of Twitter adoption may be related to the idea that politicians are adopting quickly not because of the information from past adoption outcomes, but because past adopters are high profile and well connected politicians whom potential adopters wish to connect with via Twitter. Correlated effects may come in two forms, fixed or permanent. For instance, early adopters may adopt early simply because they are comfortable with technology and therefore face the lowest intangible adoption costs; on the other hand, early adopters may adopt early because they all faced similar transitory shocks, such as a recently published news report in

[5] Refer to Scheinkman (2008) for a survey of theory behind many of these social interaction models that motivate empirical applications.

[6] Refer to Graham and Hahn (2005) for identification of a linear-in-means peer effects model with group (and individual specific) fixed effects.

the NY Times about the explosive growth of Twitter membership.

Twitter adoption in politics has also received growing attention in political science. Two recent studies by Williams and Gulati (2010) and Lassen and Brown (2010) try to characterize who adopts Twitter. Aside from finding a strong correlation between being a Republican and Twitter use, these two studies are unable to explain why some politicians adopt Twitter, while others do not. Their studies belong to the stream of research about government communications and political marketing. Research in economics about political marketing is rather scarce. One example though is research by Gordon and Hartmann (2010), who build a structural econometric model of advertising competition.

Finally, one may frame the Twitter adoption decision as Karshenas and Stoneman's (1993) interpretation of technology diffusion[7]. The authors argue that rank, stock and order effects matter in the timing of technology adoption. Rank effects are described as the inherent characteristics that differ across potential adopters, stock effects pertain to the idea that the benefit of technology adoption may fall as the number of past adopters increases, and order effects may suggest that early adopters have some form of first mover advantage.

3 Data

The setting for our analysis is the recent adoption of Twitter among members in the 111th House of Representatives. Our sample contains information about 438 politicians, 183 of whom adopted Twitter. Furthermore, the data can be broken down into four main components. Each variable is listed and described in Table 1. The first and most important subset of variables contains hand-collected information about each adopter's Twitter behavior, such as the exact date in which his/her first Twitter post was made[8], as well as the number of followers, users followed, and posts made at the time of our data collection (May 24, 2010).

[INSERT TABLE 1]

With the exception of Eric Cantor, all House Representatives adopted Twitter after President Barack Obama's first Twitter post on April 29, 2007. That said, we construct our key dependent variable, the number of days to adopt, to be equal to the number of days it took for an adopter to

[7] The literature about technology diffusion is very large. That said, refer to Federica (2002) for a general overview of these studies. On a similar note, Forman, Goldfarb, and Greenstein (2005) study the adoption of Internet across America.

[8] Note that Twitter adoption and use may not actually be done explicitly by the politician himself. It is often the case that this task is delegated to a junior level staffer. Nevertheless, the politician often has to grant this right to a staffer. Throughout the paper we refer to the adoption decision as being a decision made by the politician, although it should be perfectly clear that interns/staffers are often involved.

make his/her first Tweet, since Barack Obama's first Twitter post. As Figure 1 shows, there were not many adopters initially, followed by a gradual growth in adoption. The average adopter took about 695 days (after the President) to adopt Twitter. Clearly, the adoption of Twitter did not occur overnight.

[INSERT FIGURE 1]

From each politician's Twitter account, we are able to obtain information about how many Twitter posts he/she made since becoming a member, as well as his/her following. The status of many influential Twitter users is often measured using a popular measure of influence (Comm, 2010): the number of followers divided by the total number of Twitter posts. Presumably, those with a lot of inherent influence need not post many updates on Twitter in order to maintain a strong following. Based on this crude measure of influence, the most successful users of Twitter are Dennis Kucinich (109.6667), Eric Cantor (104.8368), Ron Paul (97.85263), Gwen Moore (92), and Alan Grayson (75.62376). Their numbers are quite significant, given that the typical politician obtains a ratio of about 13 followers per Tweet. There is a lot of variation in this ratio; much of this variation cannot be explained by when a politician adopted as Figure 2 illustrates. Adopting early does not yield an obvious first mover advantage with respect to this measure of clout.

[INSERT FIGURE 2]

The second major component of our data consists of aggregated information about his/her constituents, such as the district's average population, income and racial distribution. This information was obtained from the most recent U.S. Census. These variables may play a part in the decision to adopt, as Table 3 illustrates. Running the data through a simple probit reveals that population may be a key demographic driver in the adoption of Twitter. That is, politicians who govern heavily populated districts are more likely to adopt than those who govern smaller populations. Income and race appear to play less of a role in the adoption of Twitter.

[INSERT TABLE 3]

We also have information about each politician's personal and professional characteristics. For personal characteristics, we can identify the age, gender, race, degree type and whether he/she is Catholic. For political characteristics, we can identify whether the politician is an incumbent, his/her tenure, party allegiance, the number of bills sponsored, the number of committees assigned to, and whether he/she chairs any committee. These variables may play a role in Twitter adoption. In particular, Table 3 shows that the number of bills has a positive and significant effect on the adoption of Twitter, while being a Democrat greatly reduces the likelihood of adoption. The fact that Republicans are more active in Twitter has generated a lot of media and scholarly attention. Therefore, party allegiance would certainly be an important control to include in any analysis about the speed of adoption among adopters.

Finally, we also include dummies for whether each politician adopts MySpace, RSS, Flickr, Facebook and/or Youtube; all of which are some alternative (and older) outlets for social media. Facebook is perhaps the closest to Twitter, in terms of its functionality and the way it is used by politicians. Representatives who hold both Facebook and Twitter accounts often post identical updates on both their Facebook and Twitter pages. Furthermore, Twitter and Facebook have recently made their interfaces compatible with one another; that is, you can update your Twitter account via Facebook, and vice versa. This has created some level of synergy between the two social media outlets. On top of that, we believe that Facebook is the closest proxy one can have for indicating a politician's past knowledge/expertise with social media. Consequently, one can certainly see the complementarity between these two technologies in Table 3; a large proportion of Twitter adopters are also Facebook users. Between the two social media outlets, Facebook is the first mover, having had at least 2 years of a head start over Twitter. Not surprisingly, many of the politicians adopted Facebook well before they had the opportunity to adopt Twitter (Williams and Gulati, 2009).

[INSERT TABLE 2]

Looking at Table 2, we see that the average Twitter adopter is almost 60 years old, and has about 9 years in office. These numbers suggest that Twitter is not exclusively used by young politicians catering to their younger constituents. On average, a typical adopter is also quite active on K-Street, having sponsored about 18 bills, and being part of almost 2 committees (out of a possible 4).

4 Simple model of adoption delay

Consider a two period model in which a potential adopter's decision is whether to employ a new technology today, or tomorrow (with a discount rate of $\beta < 1$). Suppose that this potential adopter has received n signals about the technology's quality. This technology comes at no real monetary cost, and has value $\theta \sim N(0, 1/\rho_\theta)$. Each signal is defined as $s_n = \theta + \varepsilon_n$, with $\varepsilon_n \sim N(0, 1/\rho_\varepsilon)$. Denote the history of observed signals as $\boldsymbol{s}_n = \{s_1, ..., s_n\}$. Provided that the potential adopter is Bayesian, the updated mean and variance of θ are given by

$$E(\theta|\boldsymbol{s}_n) = \frac{s_1 + ... + s_n}{n}$$

$$V(\theta|\boldsymbol{s}_n) = \frac{1}{\rho_\theta + n\rho_\varepsilon}$$

Suppose that the agent has a very simple mean-variance utility,

$$E(U|\cdot) = E(\theta|\cdot) - \gamma V(\theta|\cdot)$$

where γ measures the agent's degree of risk aversion. For simplicity, set $\gamma = 1$. If the agent adopts today, he receives an expected utility of $E(U|\boldsymbol{s}_n) = E(\theta|\boldsymbol{s}_n) - V(\theta|\boldsymbol{s}_n)$. Waiting until tomorrow can yield two possible outcomes: 1) The number of signals is still n with probability λ; or 2) the number of signals has increased to $n+1$ with probability $1-\lambda$. Therefore, the utility associated with adopting tomorrow (with the information available today) is

$$\begin{aligned} E[E(U|\boldsymbol{s}_{n+1})|\boldsymbol{s}_n] &= \beta\{\lambda E(U|\boldsymbol{s}_n) + (1-\lambda)[E(\theta|\boldsymbol{s}_n) - V(\theta|\boldsymbol{s}_{n+1})]\} \\ &= \beta\{E(\theta|\boldsymbol{s}_n) + [(1-\lambda)/(\rho_\theta + (n+1)\rho_\varepsilon)]\} \end{aligned}$$

Note that the equation above uses the result that $E[E(\theta|\boldsymbol{s}_{n+1})|\boldsymbol{s}_n] = E(\theta|\boldsymbol{s}_n)$:

$$\begin{aligned} E[E(\theta|\boldsymbol{s}_{n+1})|\boldsymbol{s}_n] &= E(\frac{s_1 + ... + s_n + s_{n+1}}{n+1}|\boldsymbol{s}_n) \\ &= E(\frac{nE(\theta|\boldsymbol{s}_n) + \theta + \varepsilon_{n+1}}{n+1}|\boldsymbol{s}_n) \\ &= \frac{nE(\theta|\boldsymbol{s}_n) + E(\theta|\boldsymbol{s}_n)}{n+1} \\ &= E(\theta|\boldsymbol{s}_n) \end{aligned}$$

Therefore, the net benefit of adopting today over tomorrow is

$$NB(E(\theta|\boldsymbol{s}_n), \rho_\theta) = (1-\beta) - \frac{(1-\beta)(\rho_\theta + n\rho_\varepsilon) + (1-\beta\lambda)\rho_\varepsilon}{E(\theta|\boldsymbol{s}_n)(\rho_\theta + n\rho_\varepsilon)(\rho_\theta + n\rho_\varepsilon + \rho_\varepsilon)}$$

The first observation that comes to mind is that the constant term $(1-\beta)(\rho_\theta + n\rho_\varepsilon) + (1-\beta\lambda)\rho_\varepsilon$ is strictly greater than zero. This means that for certain values of $E(\theta|\boldsymbol{s}_n)$, the net benefit of adopting right away may be negative. However, for large enough values of $E(\theta|\boldsymbol{s}_n)$, the agent would certainly prefer to adopt today rather than tomorrow. Therefore, the incentive to adopt today increases (non-trivially) with $E(\theta|\boldsymbol{s}_n)$.

The net benefit of adopting today has limiting values of

$$\lim_{\rho_\theta \to 0} NB(E(\theta|\boldsymbol{s}_n), \rho_\theta) = \frac{n(1-\beta)[(n+1)\rho_\varepsilon - 1] - (1-\beta\lambda)}{n(n+1)\rho_\varepsilon}$$

$$\lim_{\rho_\theta \to \infty} NB(E(\theta|\boldsymbol{s}_n), \rho_\theta) = (1-\beta)$$

From these limiting values, we see that

$$\lim_{\rho_\theta \to \infty} NB(E(\theta|\boldsymbol{s}_n), \rho_\theta) - \lim_{\rho_\theta \to 0} NB(E(\theta|\boldsymbol{s}_n), \rho_\theta) = n(1-\beta) + (1-\beta\lambda) > 0$$

Therefore, the net benefit of adopting today is larger when the agent's prior is very precise (i.e. $\rho_\theta \to \infty$) as compared to when the agent's prior is very diffuse (i.e. $\rho_\theta \to 0$). Intuitively, this result should be obvious: an agent who is given a choice between a certain payoff today, versus the same payoff tomorrow should certainly choose to receive the payoff today. Further investigation of the marginal effect of $E(\theta|\boldsymbol{s}_n)$ on the net benefit of adopting today reveals additional predictions. Given that the marginal effect of $E(\theta|\boldsymbol{s}_n)$ is

$$\frac{\partial NB(E(\theta|\boldsymbol{s}_n), \rho_\theta)}{\partial E(\theta|\boldsymbol{s}_n)} = \frac{1}{E(\theta|\boldsymbol{s}_n)^2} \cdot \frac{(1-\beta)(\rho_\theta + n\rho_\varepsilon) + (1-\beta\lambda)\rho_\varepsilon}{(\rho_\theta + n\rho_\varepsilon)(\rho_\theta + n\rho_\varepsilon + \rho_\varepsilon)} > 0,$$

we can obtain its limiting values:

$$\lim_{\rho_\theta \to \infty} \frac{\partial NB(E(\theta|\boldsymbol{s}_n), \rho_\theta)}{\partial E(\theta|\boldsymbol{s}_n)} = 0$$

$$\lim_{\rho_\theta \to 0} \frac{\partial NB(E(\theta|\boldsymbol{s}_n), \rho_\theta)}{\partial E(\theta|\boldsymbol{s}_n)} = \frac{1}{E(\theta|\boldsymbol{s}_n)^2} \cdot \frac{n(1-\beta) + (1-\beta\lambda)}{n(n+1)\rho_\varepsilon} > 0$$

The marginal effect of $E(\theta|\boldsymbol{s}_n)$ is smaller when the agent's prior is very precise as compared to when his prior is very diffuse. One can show in a similar manner that the marginal effect of $E(\theta|\boldsymbol{s}_n)$ falls as the number of past signals tends to infinity. In general, favorable signals should only matter for those with little prior information.

One can also show that the net benefit is concave with respect to $E(\theta|\boldsymbol{s}_n)$ as $\frac{\partial^2 NB(E(\theta|\boldsymbol{s}_n), \rho_\theta)}{\partial E(\theta|\boldsymbol{s}_n)^2} < 0$. To summarize, this simple model generates the following testable predictions:

1. A large and favorable signal $E(\theta|\boldsymbol{s}_n)$ induces an agent to adopt the new technology sooner.

2. An agent with a precise prior ρ_θ will adopt the new technology sooner.

3. The acceleration effect that $E(\theta|\boldsymbol{s}_n)$ has on technology adoption is small for an agent with a precise prior ρ_θ.

4. The acceleration effect that $E(\theta|\boldsymbol{s}_n)$ has on technology adoption is small for an agent who has already received a large number of signals.

5. The acceleration effect is concave in $E(\theta|\boldsymbol{s}_n)$.

5 Empirical strategy

We first outline the set of regressions aimed to test the three predictions as motivated by our simple model. This is followed by proposed estimations to evaluate whether adopting after favorable information signals actually pays off. The final part discusses potential identification problems that we may face with the data.

5.1 Do favorable signals speed up Twitter adoption?

Each politician is indexed by $i = 1, ..., N$, in the order in which they adopted Twitter, 1 being the first adopter, and N being the last adopter. In our sample, $N = 183$. For each adopter i, we observe the exact date in which they adopted. Using each exact date, we construct the "days to adopt" variable, t_i, by calculating the distance between the actual date of adoption, and Barack Obama's adoption date of April 29, 2007. By construction, $t_1 < t_2 < ... < t_N$. Each politician i has access to the information signals regarding the success of past Twitter adopters, $-i$. We measure the information signal i receives using the average number of followers/Tweet for all $j < i$, denoted by f_{-i}.

Note that this measure does not perfectly capture the actual set of signals that adopter i may receive, as f_{-i} is calculated using data we collected well after their adoption decisions. Consequently, we have to make an assumption that states: f_{-i} is invariant over time. That is, the followers/Tweet we observed at the time of data collection is a good proxy for the followers/Tweets potential adopters actually observed. This assumption is potentially very unattractive, as Twitter clout can easily change over time; say, if a politician improves the content of his Twitter posts over time. One necessary condition for our assumption is that f_{-i} is the same, regardless of when the data is collected. We test our assumption using data provided by Boynton (2010) that he used in a recent study. What his data has that ours does not is an additional day in which Twitter activity is recorded. In his sample, he observes Twitter activity (i.e., followers, following, and number of Tweets) for two time periods, January and June 2009. Therefore, we can check and see whether our calculated f_{-i} is likely to vary over time. A simple correlation analysis reveals that each politician's number of followers/Tweet is almost perfectly correlated[9] between the two dates. One may then stipulate that the followers/Tweet we use based on data collected on May 24, 2010 should be a close proxy to the followers/Tweet that a potential adopter may have seen.

For each adopter i, we include controls $\boldsymbol{x}_i$ that may capture rank effects associated with technology adoption (Karshenas and Stoneman, 1993). Our prior is that we do not expect estimates of $\boldsymbol{\gamma}$ to be significant, given that recent studies in political science (Lassen and Brown, 2010; Williams and Gulati, 2010) have been rather inconclusive regarding the impact of similar explanatory variables. That said, our main regression can be written as

$$t_i = \alpha + \beta \cdot f_{-i} + \boldsymbol{x}_i'\boldsymbol{\gamma} + \varepsilon_i$$

where ε_i satisfies the usual OLS assumptions. With this regression, we can test the first prediction from our model: a large favorable signal speeds up Twitter adoption. For our data to support the prediction, we need $H_0 : \beta < 0$. That is, the earliest adopters should have followed a sequence of successful adopters with a large number of followers/Tweet.

It may also be interesting to study whether politicians discriminate across these signals. The easiest way to group the sequence of observed signals is to classify them as coming from the adopters belonging to the same or different political party as the potential adopter. Using this grouping, we construct the variables $f_{-i,own}$ and $f_{-i,other}$ to measure the average number of followers/Tweet among past adopters belonging to the same and other party as i respectively. Our model does not guide us to an obvious direction. What these variables may (or may not) tell us is whether the origin of information matters. For example, politicians from the same political party may have a greater awareness of one another, and therefore, greater awareness of their adoption outcomes. Furthermore, this specification may give us an idea about the sensitivity of our results with respect to how we group peers[10].

To test the latter two predictions from our model, we need a variable that captures a politician's prior about social media. Given the positive correlation between Facebook and Twitter adoption (Table 3), along with similar user interfaces, we argue that Facebook may be an appropriate indicator of whether a politician is familiar with the merits of social media or not. Furthermore, as Facebook adoption took place well before Twitter adoption (Williams and Gulati, 2009), concerns about simultaneity between the two decisions may not be that relevant. The reader is asked to

[9] Correlation coefficient of over 0.95.

[10] Refer to Manski (1993).

interpret Facebook adoption as such: those with Facebook accounts, and therefore, familiar with social media should have a more precise prior about the merits of Twitter than those without Facebook accounts. Therefore, setting the Facebook dummy equal to 1 is our way of approximating the case in which $\rho_\theta \to \infty$. That said, our regression to test the second and third predictions is:

$$t_i = \alpha + \beta_1 \cdot f_{-i} + \beta_2 \cdot Facebook_i + \beta_3 \cdot f_{-i} \cdot Facebook_i + \boldsymbol{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

For our data to support the second and third predictions, we need $H_0 : \beta_2 < 0$, and $H_0 : \beta_3 > 0$. Firstly, Twitter adoption should occur faster for those with Facebook accounts. Secondly, the acceleration effect that favorable past outcomes have on adoption speed should be dampened if the politician already holds a Facebook account. To test our next hypothesis, we run the following estimation:

$$t_i = \alpha + \beta_1 \cdot f_{-i} + \beta_2 \cdot (i-1) + \beta_3 \cdot f_{-i} \cdot (i-1) + \boldsymbol{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

where $(i-1)$ is the number of past adopters prior to i (i.e., the order of i's entry into Twitter). For the fourth hypothesis to hold, we need $H_0 : \beta_3 > 0$. All in all, these regressions should tell us whether adopters are making use of the information available, and whether those who appear to react strongly to this information are those who are likely to find this information valuable.

Finally, to test for concavity, we consider

$$t_i = \alpha + \beta_1 \cdot f_{-i} + \beta_2 \cdot f_{-i}^2 + \boldsymbol{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

If the relationship between adoption speed and the average of past outcomes is concave, then we would need that $H_0 : \beta_2 > 0$: the marginal impact associated with f_{-i} is largest when evaluated at small values of f_{-i}.

5.2 Are favorable signals from the past associated with successful Twitter adoption today?

The estimations above tell us nothing about whether politicians are using their available information to increase their payoff. In this section, we outline the strategy used to assess whether politicians are making use of their information. Although we have no way of measuring the channels between information and adoption, then adoption to success, we can analyze the direct channel between past information and own success. Our model stipulates that those who receive positive signals are more likely to enter earlier. This behavior should intuitively generate a positive correlation between positive signals and own success should they be acting optimally.

Denoting own success at attaining followers/Tweet as f_i, we carry out the following estimation

$$f_i = \alpha + \beta \cdot f_{-i} + \boldsymbol{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

If favorable past signals are any indication of own success, we should see $H_0 : \beta > 0$. We repeat the same exercise as the previous section by running similar regressions that involve $f_{-i,own}$ and $f_{-i,other}$, as well as regressions that include interaction terms between Facebook adoption and f_{-i}.

5.3 Identification

Although our data puts us in a unique position to analyze the impact of past available information on adoption speed, there are a number of issues that may prohibit us from clean identification. We now outline the numerous problems that may weaken our results, as well as ways in which we address them.

5.3.1 Unobserved heterogeneity

The data we use contains a lot of information about each politician. Nevertheless, a rich set of covariates is an insufficient solution to unobserved heterogeneity. It could very well be that those who face low and unobserved adoption costs are also those who also likely to generate observed favorable signals. Low adoption costs may also be correlated with their technologically savvy. Furthermore, those with low adoption costs are also likely to enter the Twittersphere first. Therefore, those with low (but not the lowest) adoption costs who immediately follow these technologically politicians need not be doing so because of the favorable information they receive, but because they themselves also have low adoption costs. Without panel data, it is difficult to address these concerns.

Our prescription is to make two assumptions about the individual fixed effect, ω_i. The first assumption is that it monotonically increases with i. That is, it can be interpreted as: politicians who adopt later may also be those who have high adoption costs, characterized by the fixed effect. The second assumption is that each individual's fixed effect is equally spaced; i.e., $\omega_i - \omega_{i-1} = \kappa$. These two assumptions allow us to write the fixed effect recursively as $\omega_i = (i-1)\kappa + \omega_1$. Including this term into the original estimation equation yields

$$t_i = (\alpha + \omega_1) + \beta \cdot f_{-i} + \boldsymbol{x}_i' \boldsymbol{\gamma} + (i-1)\kappa + \varepsilon_i$$

While this approach does not free us completely of issues related to unobserved heterogeneity, it provides us some way to add skepticism/conservatism to the estimates for β. In some respects, the inclusion of each adopter's order of entry captures both the order and stock effects as described by Karshenas and Stoneman (1993).

5.3.2 Correlated errors

Adoption time is at a granular level, and the time of adoption between two adopters can potentially be just days, so we should expect that the error terms of consecutive adopters may be correlated. For instance, those who adopted on different days, but within the same week may have received similar information shocks about the use of Twitter in politics, say, through the NY Times or Wall Street Journal. The impact of past shocks may confound our identification of the so-called acceleration effect. Positive shocks that affected past adopters may have coincidentally boosted their followers/Tweet, may also induce subsequent adopters to enter soon after; therefore, early entry need not be explained by the presence of favorable information through past adopters' outcomes, but instead by the presence of favorable information through some other mechanism, say news media, that simply carries over through time.

To address this relevant concern, we allow the error terms to be serially correlated with an AR(1) process. Therefore, we estimate

$$t_i = \alpha + \beta \cdot f_{-i} + \boldsymbol{x}_i' \boldsymbol{\gamma} + \varepsilon_i$$

$$\varepsilon_i = \rho \varepsilon_{i-1} + \nu_i$$

where ν_i is assumed to be white noise. Recall that each adopter is ordered, so we are essentially specifying an empirical model that allows a current adopter's error to depend on the error associated with those before him/her.

5.3.3 Selection bias

Our sample of Twitter adopters is a selected sample among the entire population of congressional members. Using a similar argument as our discussion about unobserved heterogeneity, early adopters may not necessarily be reacting to positive information shocks, but instead, to their own ability to use social media.

We can interpret the adoption and timing decisions as a two-step process. In the first step, a representative decides whether to open up a Twitter account. Once they have decided to become a member, they must decide when. The first stage decision can be modelled using the Probit estimates obtained in Table 3. This first stage will provide us the Heckman correction term as described by the Mills ratio $\frac{\hat{\phi}_i}{\Phi_i}$ from the first-stage adoption Probit estimates. To correct for this sample selection bias, we estimate the following second-stage regression with a Heckman correction term

$$t_i = \alpha + \beta \cdot f_{-i} + \boldsymbol{x}_i'\boldsymbol{\gamma} + \lambda \cdot \frac{\hat{\phi}_i}{\Phi_i} + \varepsilon_i$$

An analogous strategy is employed for the analysis of own followers/Tweet.

5.3.4 Temporal factors

There is a clustering of Twitter adoption around the beginning of session, January 20, 2009. Therefore, we have cause for concern that some of these late adopters may not be adopting late because of bad signals, but simply because it was when congressional staffers were hired and assigned to manage members' Twitter accounts. We consider a sub-sample of politicians for which their adoption decisions are unlikely to be affected by this temporal shock: the sub-sample of politicians who entered Twitter, but not around the start of session within a 200 day window (i.e., 100 days before January 20, 2009, and 100 days after that date).

One may also argue that the measure f_{-i} is very inaccurate for the initial adopters, as the averages may be computed with very few observations. This measure may therefore lack credibility for the earliest Twitter users. Consequently, we consider using estimations using only the sub-sample of adopters who follow at least 50 past users. Using this approach, we ensure that each politician's signal is calculated using at least 50 observations.

5.3.5 Contextual effects

As we are looking at the average outcomes of past adopters, our analysis can be framed under Manski's (1993) linear peer effects model. To some extent, the sequential and granular nature of our data frees us of some issues related to simultaneity of adoption decisions. What remains to be shown is that our results are robust to the correlated and contextual effects. Correlated effects describe the fact that early adoption may not be caused by favorable information shocks from their peers, but instead, the fact that early adopters share similar unobserved benefits/costs associated with Twitter adoption.

These unobserved components can either have a permanent component, or transitory component. For example, the 10th adopter may have opened up a Twitter account early because he behaves in the same way as other tech savvy politicians. To some extent, permanent unobserved group effects can be addressed using our earlier prescription for unobserved heterogeneity: controlling the order of entry may also control for these permanent correlated effects across adopters among similar cohorts. Transitory group effects may include the fact that early adopters face similar idiosyncratic shocks as other early adopters. This identification problem can be framed using our solution to correlated errors. Finding a large estimate for ρ would suggest that these unobservable group effects persist over time.

If contextual effects matter, these effects may even proxy for network externalities. Past adopters who happen to also come from Ivy league schools may have stronger alumni ties. These ties would be correlated with their own popularity on social media sites, like Twitter. Potential adopters may be induced to enter early not because of this observed Twitter clout, but because they wish to reach out to these well-connected Ivy league politicians via Twitter. To some extent, the characteristics of past adopters may partially (but not completely) control for motives associated with network effects.

In order to control for these contextual effects, we include average characteristics of all past adopters, $\boldsymbol{x}_{-i}$ into the following regression

$$t_i = \alpha + \beta \cdot f_{-i} + \boldsymbol{x}_i' \boldsymbol{\gamma} + \boldsymbol{x}_{-i}' \boldsymbol{\psi} + \varepsilon_i$$

6 Main results

Many of our results support the predictions generated by the model. In the first column of Table 4, we see that increasing the followers/Tweet signal by 8 yields a statistically significant decrease in adoption time by nearly 112 days. Given that the average adopter takes about 695 days to adopt, this would amount to a reduction in delay by over 10%. Interestingly, the politicians do not appear to be discriminating across signals based on party lines, in that signals coming from their own and other party have about the same impact.

An unexpected result in the first two columns is that Facebook adoption increases delay by over 58 days. It is quite possible that Facebook is a close substitute for Twitter, in that loyal Facebook users may find it hard to allocate time to Twitter use.

[INSERT TABLE 4]

According the third and fourth columns, having a Facebook account speeds up the adoption of Twitter by at least 147 days. Our results are consistent with the idea that Facebook account holders likely have a more precise prior about the value of Twitter, and therefore, have less incentive to delay for the possibility of more information. Furthermore, we find that the acceleration effect associated with the past adopters' signals is dampened by about 20 days for Facebook users.

Interestingly, when signals are categorized by party, we find that holding a Facebook account dampens the acceleration effect associated with the averaged signals from adopters belonging to the same party, but not for the averaged signals from adopters belonging to a different party. This result, found in the fourth column of Table 4, suggests that while politicians do not appear to be discriminating signals based on parties, the way in which they use these signals may differ depending on where these signals come from. One possible explanation is that the signals coming from a rival party do not enter a politician's utility through a learning mechanism, but instead through a competition model, in which a politician feels pressure to compete for attention against his/her ideological rivals who have already garnered significant visible support on Twitter.

[INSERT TABLE 5]

Table 5 reveals that the interaction between an adopter's order (i.e., the number of those preceding him) and the average number of followers/Tweet among past adopters has a positive and significant coefficient. This finding provides some support for the fourth hypothesis generated by our simple model. Unlike the interactions between Facebook adoption and positive information signals, we find that the dampening effect associated with the number of past adopters has the expected sign regardless of whether they are interacted with the signals coming from those of the same or other political party.

[INSERT TABLE 6]

The effect associated with the squared average followers/Tweet is estimated to be positive and significant in the first column of Table 6. This means that the acceleration effect has its greatest marginal impact for small values of this average of past outcomes. Our finding here is consistent with the hypothesis which states that the marginal effect associated with past outcomes is concave.

The estimates for our control variables are in general quite noisy. Nevertheless, some have interesting signs. Members who belong to a large number of committees tend to take longer to adopt Twitter. This may highlight the fact that being in a number of committees results in a larger workload/responsibility, and therefore, less time/resources to devote towards social media management. It is also worth noting that not only are Democrats less likely to adopt Twitter (Table 3), they are also slower at adopting Twitter.

Our estimates in the first two columns of Table 7 reveal a strong relationship between a politician's own realized number of followers/Tweet, and the average followers/Tweet of adopters prior to him/her. An increase in the past adopters' aggregated signal by 8 yields an increase in own followers/Tweet by over 8. This effect is slightly more pronounced when the signals come from past adopters' belonging to the same party, as shown in the second column. When the Facebook adoption interactions are introduced, the acceleration effect is slightly smaller; but this is perhaps because the interacted term between Facebook adoption and past adopters' signal is also positive. Indeed, those who receive favorable signals and are Facebook adopters than those who receive favorable signals but are not Facebook adopters.

[INSERT TABLE 7]

The model presented earlier cannot explain this result. Nevertheless, the observed phenomenon may still be consistent with the idea of Facebook as an indicator for preciseness of a politician's prior on social media value. Politicians who are more comfortable with social media may be able to better utilize the information available to them, while politicians who are not as comfortable with social media, while reacting strongly to positive signals, may not turn their adoption decision into realized success. Although past adopters' provide some idea as to the demand for politicians on Twitter, much of a politician's success on Twitter largely depends on his/her inherent ability to keep followers captivated with insightful and informative Twitter updates.

[INSERT TABLE 9]

Our sensitivity analysis displayed in Table 9 reveals that the estimates for the acceleration effect are of the correct sign and statistically significant regardless of whether our regression accounts for unobserved heterogeneity, autocorrelation, or self selection. Note however that the magnitude of the effect drops significantly when we allow the error terms to have an AR(1) structure. In fact, we find that the magnitude of a the effect falls to about 3 days (for an increase of 8 average followers/Tweet for past adopters). Furthermore, the Durbin-Watson test leads to a rejection of the null hypothesis of no autocorrelation. Therefore, much of the effect associated with the past adopters' aggregate signal confounds temporal shocks. Nevertheless, we find it encouraging that the signals still play some, albeit small, role in the timing decision for Twitter adoption when correlated errors are introduced.

[INSERT TABLE 10]

Table 10 shows that for the most part, our results regarding own success are robust to the aforementioned identification problems. The estimated positive effect of past adopters' success on a current adopter's own success falls under the AR(1) model; note however that we are unable to reject the null hypothesis of no autocorrelation using the Durbin-Watson test. Therefore, the results in the second column lack statistical credibility.

[INSERT TABLES 11 AND 12]

Our results are preserved when we only use sub-samples of our original sample. The first column of Table 11 shows that the acceleration effect holds even when we only consider adopters who started using Twitter outside the time interval surrounding the start of office. Similarly, the second column of Table 11 demonstrates that this effect holds when we exclude the earliest adopters, who have very little past adoption information to go on. Much the same can be said for the results in Table 12, which show that the favorable information from the past lead to better realized outcomes.

[INSERT TABLE 13]

The effect of past adopters' success appears to be preserved when we add contextual effects as the last column of Table 13 shows. Nevertheless, some of the estimated contextual effects are worth mentioning. The strongest contextual effects are the average number of incumbents and the average number of committee chairs. Increasing the average proportion of incumbents by one standard deviation speeds up the time of adoption by 476 days, and increasing the average proportion of committee chairs by one standard deviation speeds up adoption by at least 75 days. The average proportion of past adopters who are black, Catholic, law degree holders and Ivy league graduates also accelerate the adoption process. All in all, these contextual effects are consistent with our intuition that some politicians may be adopting Twitter not only because of the information they receive from their peers, but also to connect with their peers; especially those with political power (i.e., incumbents and chairs), and those with access to rich social networks (i.e., former lawyers and Ivy league alumni). Our analysis also suggests that politicians may benefit from these contextual effects. Table 14 hows that their realized number of followers/Tweet is positively associated with the average number of Catholics and Ivy league alumni among past adopters, as well as the average number of adopters who are chairs of congressional committees.

[INSERT TABLE 14]

What makes these contextual effects compelling is the observation that own characteristics are unable to explain adoption timing nor own adoption success. Consequently, a finding like this also limits our ability to say that social learning is the only story behind the patterns we observe: the alternative explanation involving network externalities is certainly plausible, as peer characteristics related to skill (i.e., political power) and peer characteristics related to networking (i.e., social characteristics) matter. Not surprisingly, the effect associated with past information falls as more and more of these contextual effects are included to each regression. This pattern may reflect the idea that our initial estimates confound both learning and network effects.

6.1 Extensions

In this subsection, we evaluate alternative interpretations of how politicians use the information they have at their disposal. For much of our analysis, we have assumed that the information signals are in the form of averaged past outcomes. This specification may be dubious for a few reasons. First, politicians may only have knowledge of recent signals; second, politicians may react to these signals only if past information has the potential to change their prior (i.e., positive/negative surprises); and third, information quality may vary depending on the geographic distance of these signals.

6.1.1 New information vs old information

Our analysis certainly suggests that the success of past adopters plays some role in the timing decision of Twitter adoption. What we don't know though is whether politicians take into account all of the signals. It is no plausible that the politicians or their staffers will pay attention to the success rates for each and every past adopter; especially for the late adopters who have over 100 possible signals to take in. In this section, we wish to test the hypothesis that only recent signals matter. To test this hypothesis, we compare the following specifications:

1. One in which we only consider the 10 most recent past adopters when calculating the average followers/Tweet.

2. One in which we only consider the 20 most recent past adopters when calculating the average followers/Tweet.

3. One in which we consider the latter 10 (of the 20 most recent) past adopters when calculating the average followers/Tweet.

When we pass the data through these three different specifications, some interesting patterns emerge as displayed in Table 15. First, the effect associated with past adoption success is stronger for the first specification than for the latter. This pattern means that when looking at the 20 most recent adopters, politicians more strongly to the 10 most recent outcomes than to the 10 latter outcomes. Under the sequential learning paradigm, this result would suggest that newer information matters more. However, the effect is strongest in the second specification, in which all of the 20 recent outcomes are included when calculating the average. Although newer information trumps older information, politicians are not acting as though old information is completely useless.

[INSERT TABLES 15 AND 16]

As shown in Table 16, the effect associated with the average followers/Tweet among recent adopters is negative across the board. Note however that the last specification yields the least negative effect, and the second specification yields the largest negative effect. Using recent information would not yield much of a payoff, especially if there are few observations to go by and if the information is based on relatively outdated outcomes.

6.1.2 Positive and negative surprises

We now attempt to identify whether each politician's realized number of followers/Tweet was a positive or negative surprise given his ex ante expectation. It is of course impossible to perfectly estimate each politician's expectation; however, we can obtain predicted values, $E(f_i)$, of the realized followers/Tweet using the estimates from Table 6. Using this proxy for expected success, we identify a positive surprise as the case when the realized followers/Tweet exceeds a politician's expectation, $f_i - E(f_i) > 0$, and a negative surprise if the opposite is true, $f_i - E(f_i) < 0$. With these values, we can then approximate the average proportion of positive (and negative) surprises among past adopters.

Intuitively, we should see that an increase in the proportion of positive surprises have a similar impact as an increase in the expected value associated Twitter adoption. The opposite should hold with respect to negative surprises. Framing our analysis in this manner gives us the ability to check how sensitive our results are to the interpretation of ex ante expectations.

[INSERT TABLE 17]

Table 17 suggests that positive surprises behave in a similar manner as an increase in the average number of followers/Tweet among past adopters. A standard deviation increase in the percentage of positive surprises yields a decrease in adoption time by about 256 days. Negative surprises have the opposite effect: an increase in the percentage of negative surprises yields an increase in adoption time by about 23 days. Here we see that politicians react more strongly to positive surprises, than to negative surprises.

6.1.3 Does geography matter?

Earlier analysis has already shown that politicians do not discriminate between information from past outcomes of peers who belong to the same political party, and past outcomes of peers who belong to a different party. But the same may not be true if politicians have an opportunity to discriminate based on geography. The relationship between geographic distance and information quality is well established (Malloy, 2005), so we would expect that politicians prefer to synthesize information from sources nearest them. Although the past outcomes are observable to all, there may be additional parcels of information that cannot be conferred through this statistic alone; such as details regarding functionality, suggested Twitter topics, and general sentiment among constituents who discuss politics on Twitter.

[INSERT TABLES 18 AND 19]

In this extension, we consider the possibility that politicians discriminate across signals based on whether these signals come from past adopters who govern districts within the same state, or whether these signals originate from outside their respective home states. Tables 18 and 19 display the results from our estimations using these new definitions for past adoption success. In general, politicians react similarly to both sources of information. The difference is the magnitude to which they speed up adoption. We find that a standard deviation change by 5 followers/Tweet among politicians belonging to a different state yields 3 times the effect than that associated with the same change to the followers/Tweet among politicians within the same state. One alternative explanation for this observation is that Twitter is also used to maintain connections between politicians and citizens outside of their main constituent base. By reaching out to constituents belonging to districts of their peers, a politician may achieve greater success at coercing his rivals to support contentious bills/policies by first establishing a "grassroots" movement in districts beyond their jurisdiction.

Note however that when we analyze the impact of past adoption success on own realized success, we are only able to find a positive relationship between own success and favorable information coming out of the same state. This finding suggests that politicians are using information from different sources differently. The fact that politicians accelerate adoption in light of good signals near them, and that these good signals also benefit them ex post provides some evidence of informational advantage based on geography. We can only conjecture the exact motivation behind rapid adoption in light of good signals coming outside of their state.

7 Conclusion

Our analysis exploits a unique feature about the adoption of Twitter in Congress: knowing the exact date of adoption allows us not only to analyze the speed of adoption, but all the information available at the time of adoption. Knowing who the past adopters are, as well as their success at attaining followers/Tweet, gives a current adopter valuable information about the value of Twitter as a mode for influence. Twitter is primarily a broadcasting device for politicians (Golbeck, Grimes and Rogers, 2010), so being able to assess its outreach capabilities is especially important to politicians.

Guided by our simple model of adoption delay, we find that favorable information leads to quicker adoption, and especially so for those who have diffuse priors. Furthermore, we find that politicians who adopt Twitter after receiving favorable information signals benefit via increased clout for their own Twitter presence upon adoption. Although our results are suggestive of social learning, we cannot completely rule out alternative explanations such as network externalities.

The unique feature of our data suffers from some of the problems associated with time series analysis. Given that the adoption decisions are at times clustered near one another, persistent temporal shocks limit our ability to make any strong statements regarding the impact of information on adoption speed. In spite of this limitation, we are still able to produce an acceleration effect consistent with our model's main prediction.

Although our extensions explore different avenues to which these signals affect politicians, our analysis assumes away learning within well-defined social networks. Although politicians do not appear to react differently to signals coming from different parties, it is plausible that they may react strongly to signals coming from those they frequently contact. Some possible networks/groupings that could be considered may be based on the congressional committees. A challenge of using these definitions is that network/group formation likely takes place around the same time as Twitter adoption. Instead, future work could incorporate the use of alumni networks, as in Cohen and Malloy (2010), and investigate whether signals coming from alumni connections have a stronger effect at accelerating Twitter adoption than signals coming outside the alumni network.

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Table 1: Variable definitions

Variable	Description
Days to adopt	Days it takes politician to adopt relative to Barack Obama's first Tweet
f_i	Ratio of followers per Tweet for i
f_{-i}	Average ratio of followers per Tweet for adopters prior to i
$f_{-i,own}$	Average ratio of followers per Tweet for adopters in same party as i
$f_{-i,other}$	Average ratio of followers per Tweet for adopters in different party as i
Month-time	Discretized time variable at a monthly level
log(Population)	Log of the population for politician i's governing district
log(Income)	Log of the income for politician i's governing district
Percentage black	Percentage of Black constituents in politician i's governing district
Gender	Dummy set equal to 1 if female
Black	Dummy set equal to 1 if black
Catholic	Dummy set equal to 1 if Catholic
Law	Dummy set equal to 1 if holds law degree
Ivy	Dummy set equal to 1 if holds degree from an Ivy League school
Age	Age of politician
Incumbent	Dummy set equal to 1 if politician was in office prior to the 2008 elections
Tenure	How many years a politician has been in office
Democrat	Dummy set equal to 1 if belongs to Democratic party
Bills	The total number of bills introduced by politician
Chair	Dummy set equal to 1 if chairs a committee
Number of committees	The total number of committees that politician belongs to
MySpace	Dummy set equal to 1 if holds a MySpace account
RSS	Dummy set equal to 1 if holds an RSS account
Flickr	Dummy set equal to 1 if holds a Flickr account
Facebook	Dummy set equal to 1 if holds a Facebook account
Youtube	Dummy set equal to 1 if holds a Youtube account

Table 2: Summary statistics.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Days to adopt	695.148	200.487	-2	1116
f_i	12.946	17.145	1.0813	109.667
f_{-i}	11.629	6.932	5.409	104.837
$f_{-i,own}$	11.417	7.306	4.111	104.837
$f_{-i,other}$	12.2	5.913	0	55.731
Month-time	17.352	6.089	2	36
log(Population)	13.364	0.214	10.96	15.2
log(Income)	10.643	0.262	9.620	11.43
Percentage black	12.637	15.963	0	96.400
Gender	0.167	0.373	0	1
Black	0.082	0.275	0	1
Catholic	0.292	0.455	0	1
Law	0.352	0.478	0	1
Ivy	0.098	0.298	0	1
Age	57.333	10.16	28	86
Incumbent	0.861	0.347	0	1
Tenure	9.550	8.711	0	54
Democrat	0.598	0.491	0	1
Bills	18.018	12.45	0	96
Chair	0.103	0.304	0	1
Number of committees	1.936	0.826	0	4
MySpace	0.014	0.116	0	1
RSS	0.573	0.495	0	1
Flickr	0.151	0.358	0	1
Facebook	0.571	0.496	0	1
Youtube	0.731	0.444	0	1
N		183		

Table 3: Characterization of who adopts Twitter using a Probit model of adoption. Dependent variable is equal to 1 if politician adopts Twitter.

	(1)	
	Adopt Twitter	
log(Population)	0.872*	(0.378)
log(Income)	0.0921	(0.287)
Percentage black	0.00616	(0.00548)
Gender	0.214	(0.180)
Black	-0.427	(0.326)
Catholic	0.0892	(0.159)
Law	0.0402	(0.144)
Ivy	0.377	(0.227)
Age	-0.0120	(0.00791)
Incumbent	-0.336	(0.216)
Tenure	-0.00844	(0.0113)
Democrat	-0.932***	(0.160)
Bills	0.0184**	(0.00559)
Chair	-0.0244	(0.234)
Number of committees	-0.0391	(0.0865)
MySpace	0.820	(0.728)
RSS	0.220	(0.142)
Flickr	0.405*	(0.188)
Facebook	0.702***	(0.153)
Youtube	0.120	(0.177)
Constant	-12.39*	(5.831)
Observations	438	
R^2	0.2051	

Robust standard errors in parentheses

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

Table 4: The relationship between the speed of adoption and the follower success of past adopters. Days to adopt is defined as the total number of days it takes politician i to adopt relative to Barack Obama's first Tweet on April 29, 2007.

	(1)		(2)		(3)		(4)	
	Days to adopt		Days to adopt		Days to adopt		Days to adopt	
Month-time	5.718***	(1.077)	3.883***	(0.809)	5.429***	(0.950)	3.706***	(0.736)
log(Population)	-47.20	(36.46)	-43.88	(29.87)	-67.77	(34.52)	-62.86*	(24.83)
log(Income)	-53.02	(43.06)	-52.36	(36.37)	-66.99	(40.43)	-64.86	(34.25)
Percentage black	-0.281	(0.680)	-0.413	(0.528)	-0.237	(0.647)	-0.707	(0.482)
Gender	30.95	(26.37)	14.44	(20.69)	32.06	(25.11)	13.95	(19.46)
Black	-30.66	(38.98)	-34.71	(31.68)	-32.41	(37.28)	-17.94	(32.76)
Catholic	-5.102	(26.24)	-8.413	(19.37)	14.17	(24.53)	-4.256	(17.75)
Law	2.821	(21.16)	2.911	(17.21)	7.974	(19.53)	5.017	(15.75)
Ivy	32.36	(42.03)	13.25	(32.12)	1.530	(31.99)	-8.901	(28.20)
Age	0.904	(1.139)	0.745	(0.856)	0.884	(1.049)	0.889	(0.783)
Incumbent	-23.40	(24.88)	-0.206	(19.75)	-43.53	(23.23)	-7.209	(19.25)
Tenure	2.803	(1.875)	1.091	(1.408)	4.227*	(1.671)	1.076	(1.395)
Democrat	43.51	(26.41)	17.40	(25.61)	40.02	(24.52)	8.253	(23.15)
Bills	-1.070	(0.894)	-0.451	(0.675)	-0.903	(0.853)	-0.327	(0.575)
Chair	-7.556	(44.00)	16.61	(30.19)	-5.171	(42.45)	7.640	(27.43)
Number of committees	11.98	(10.82)	12.34	(8.340)	9.446	(9.802)	5.600	(7.657)
MySpace	-59.52	(31.36)	-32.56	(21.67)	-66.15	(35.21)	-33.40	(20.63)
RSS	-7.650	(22.31)	1.941	(16.84)	1.406	(21.34)	10.54	(15.73)
Flickr	-32.57	(26.00)	-33.23	(20.29)	-42.69	(24.82)	-39.86	(20.52)
Facebook	77.35**	(28.42)	58.30**	(20.86)	-285.8***	(73.29)	-147.6	(79.01)
Youtube	-31.67	(42.55)	-24.28	(31.65)	-29.29	(39.14)	-32.03	(26.67)
f_{-i}	-14.42**	(4.964)			-32.32***	(2.527)		
$f_{-i,own}$			-16.45***	(3.623)			-28.23***	(1.993)
$f_{-i,other}$			-19.16***	(1.637)			-19.01***	(1.647)
Facebook * f_{-i}					20.96***	(4.378)		
Facebook * $f_{-i,own}$							13.67***	(3.394)
Facebook * $f_{-i,other}$							-1.843	(2.841)
Constant	1956.7*	(784.9)	2298.4***	(664.6)	2697.7***	(766.3)	2911.0***	(604.0)
Observations	183		183		183		183	
R^2	0.5874		0.7639		0.6649		0.8067	

Robust standard errors in parentheses

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

Table 5: The relationship between the speed of adoption and the follower success of past adopters. Days to adopt is defined as the total number of days it takes politician i to adopt relative to Barack Obama's first Tweet on April 29, 2007.

	(1)		(2)		(3)		(4)	
	Days to adopt		Days to adopt		Days to adopt		Days to adopt	
$(i-1)$	3.117***	(0.153)	2.957***	(0.272)	0.369	(1.241)	1.371	(0.984)
Month-time	-1.905**	(0.574)	-1.628*	(0.680)	-1.571**	(0.595)	-1.502*	(0.732)
log(Population)	-21.92	(17.14)	-17.66	(19.75)	-19.80	(16.89)	-24.71	(21.12)
log(Income)	-15.86	(20.28)	-23.14	(22.89)	-16.87	(19.66)	-26.09	(22.73)
Percentage black	-0.434	(0.330)	-0.549	(0.365)	-0.459	(0.331)	-0.547	(0.381)
Gender	-1.308	(10.68)	-0.460	(11.03)	-0.757	(10.44)	-3.093	(11.25)
Black	-11.32	(20.63)	-5.227	(22.74)	-14.55	(19.53)	-12.08	(22.73)
Catholic	-24.27*	(10.80)	-25.40*	(11.33)	-22.59*	(10.53)	-22.68*	(11.29)
Law	-3.578	(9.282)	-6.744	(9.655)	-7.072	(9.285)	-8.657	(9.821)
Ivy	6.284	(13.68)	4.192	(14.39)	3.989	(13.36)	0.950	(14.53)
Age	-0.356	(0.526)	0.0305	(0.588)	-0.470	(0.520)	-0.289	(0.572)
Incumbent	6.572	(11.78)	8.273	(12.95)	4.369	(11.75)	3.387	(13.07)
Tenure	-0.881	(0.827)	-1.242	(0.947)	-0.549	(0.803)	-0.897	(0.904)
Democrat	2.681	(9.888)	16.83	(16.88)	3.892	(9.879)	-17.58	(28.44)
Bills	0.311	(0.278)	0.285	(0.283)	0.382	(0.274)	0.431	(0.300)
Chair	9.975	(15.11)	8.018	(14.89)	6.164	(14.80)	5.947	(14.53)
Number of committees	0.642	(5.402)	1.059	(5.590)	-0.789	(5.277)	-0.267	(5.518)
MySpace	34.72	(28.17)	35.16	(29.73)	34.26	(25.07)	40.28	(26.16)
RSS	3.494	(10.23)	4.377	(10.54)	4.396	(10.28)	6.080	(10.78)
Flickr	-3.440	(11.06)	-7.234	(12.35)	0.682	(11.17)	-5.066	(12.23)
Facebook	24.32*	(10.66)	24.85*	(11.71)	21.56*	(10.09)	25.97*	(11.11)
Youtube	-17.08	(14.72)	-24.06	(15.18)	-20.95	(14.72)	-28.29	(16.19)
f_{-i}	-6.707***	(1.621)			-6.119***	(1.534)		
$f_{-i,own}$			-6.615***	(1.543)			-6.135***	(1.449)
$f_{-i,other}$			-3.065	(3.141)			-1.963	(2.952)
$(i-1) * f_{-i}$					0.230*	(0.105)		
$(i-1) * f_{-i,own}$							0.115*	(0.0548)
$(i-1) * f_{-i,other}$							0.0242	(0.0380)
Constant	1027.0**	(379.6)	1091.4*	(446.9)	960.5*	(373.7)	1182.3*	(454.5)
Observations	183		183		183		183	
R^2	0.9302		0.9190		0.9324		0.9223	

Robust standard errors in parentheses

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

Table 6: The relationship between the speed of adoption and the follower success of past adopters. Days to adopt is defined as the total number of days it takes politician i to adopt relative to Barack Obama's first Tweet on April 29, 2007.

	(1) Days to adopt		(2) Days to adopt	
Month-time	3.514***	(0.749)	2.909***	(0.692)
log(Population)	-63.23*	(24.38)	-32.71	(24.06)
log(Income)	-28.34	(34.08)	-40.87	(28.40)
Percentage black	-0.678	(0.492)	-0.784	(0.481)
Gender	12.82	(17.94)	11.51	(16.84)
Black	-11.34	(27.78)	-7.768	(31.04)
Catholic	3.820	(17.54)	-9.755	(16.65)
Law	-0.465	(14.66)	-7.316	(13.82)
Ivy	-33.47	(26.10)	-18.02	(25.82)
Age	0.462	(0.706)	1.361	(0.794)
Incumbent	-17.25	(18.21)	3.774	(17.88)
Tenure	1.678	(1.325)	-0.0986	(1.317)
Democrat	36.22*	(18.32)	70.25**	(26.34)
Bills	-0.225	(0.562)	-0.105	(0.463)
Chair	3.221	(27.58)	8.079	(22.08)
numcommittees	4.518	(7.541)	7.058	(7.469)
MySpace	-45.49*	(21.35)	-24.92	(23.44)
RSS	4.860	(16.93)	5.021	(13.46)
Flickr	-11.09	(18.47)	-26.95	(16.92)
Facebook	26.93	(16.78)	31.56*	(15.28)
Youtube	-38.78	(28.59)	-45.96	(23.80)
f_{-i}	-51.72***	(5.325)		
f^2_{-i}	0.381***	(0.0429)		
$f_{-i,own}$			-36.88***	(2.657)
$f_{-i,other}$			-18.41***	(5.376)
$f^2_{-i,own}$			0.219***	(0.0239)
$f^2_{-i,other}$			0.00115	(0.0819)
Constant	2498.3***	(639.6)	2289.4***	(557.5)
Observations	183		183	
R^2	0.8201		0.8502	

Robust standard errors in parentheses

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

Table 7: The relationship between own follower success and the follower success of past adopters. Followers/Tweet (f_i) is an approximation based on the total number of followers divided by the total number of Twitter posts at the time of data collection.

	(1)		(2)		(3)		(4)	
	Followers/Tweet		Followers/Tweet		Followers/Tweet		Followers/Tweet	
Days to adopt	0.0130	(0.0109)	0.0324**	(0.0103)	0.00439	(0.0130)	0.0295*	(0.0117)
Month-time	0.0681	(0.146)	0.0490	(0.140)	0.104	(0.151)	0.0745	(0.147)
log(Population)	-6.064	(4.360)	-6.344	(3.963)	-7.411	(4.579)	-6.866	(4.292)
log(Income)	-7.466	(4.486)	-6.484	(4.137)	-8.560	(4.683)	-7.415	(4.347)
Percentage black	-0.197	(0.106)	-0.177	(0.101)	-0.198	(0.106)	-0.156	(0.0966)
Gender	0.954	(2.810)	0.857	(2.793)	1.271	(2.738)	1.148	(2.754)
Black	8.369	(10.91)	8.512	(10.65)	8.025	(10.92)	7.705	(10.57)
Catholic	0.857	(2.664)	1.465	(2.632)	1.695	(2.751)	2.103	(2.690)
Law	-1.138	(2.566)	-0.786	(2.567)	-0.878	(2.551)	-0.809	(2.641)
Ivy	5.924	(5.726)	5.552	(5.643)	4.791	(5.980)	4.622	(6.097)
Age	0.138	(0.156)	0.0919	(0.155)	0.145	(0.157)	0.0988	(0.156)
Incumbent	0.292	(3.103)	-0.548	(3.076)	-0.830	(3.216)	-1.551	(3.238)
Tenure	-0.172	(0.173)	-0.112	(0.163)	-0.0830	(0.179)	-0.0145	(0.173)
Democrat	0.606	(2.903)	-1.270	(3.194)	0.820	(2.849)	-0.341	(3.307)
Bills	0.156	(0.152)	0.150	(0.149)	0.155	(0.146)	0.142	(0.141)
Chair	-3.116	(3.880)	-3.057	(3.844)	-3.071	(3.578)	-3.076	(3.718)
Number of committees	0.188	(1.115)	0.133	(1.082)	0.175	(1.078)	0.344	(1.056)
MySpace	22.91**	(7.740)	22.73**	(7.229)	22.10**	(7.482)	21.77**	(7.144)
RSS	0.291	(2.909)	0.363	(2.899)	0.640	(2.869)	0.306	(2.841)
Flickr	-4.951*	(2.124)	-4.014*	(2.025)	-5.694*	(2.224)	-4.504*	(2.046)
Facebook	-4.192	(4.403)	-4.836	(4.263)	-20.14*	(9.283)	-28.99	(16.38)
Youtube	-0.846	(4.953)	0.487	(4.587)	-1.009	(4.818)	0.855	(4.359)
f_{-i}	1.059***	(0.188)			0.116	(0.487)		
$f_{-i,own}$			1.454***	(0.237)			0.974	(0.535)
$f_{-i,other}$			0.941*	(0.385)			0.405	(0.338)
Facebook * f_{-i}					0.959	(0.511)		
Facebook * $f_{-i,own}$							0.568	(0.530)
Facebook * $f_{-i,other}$							0.839	(0.514)
Constant	141.9	(92.96)	101.7	(79.06)	192.6	(104.0)	136.6	(93.28)
Observations	183		183		183		183	
R^2	0.2827		0.3216		0.3007		0.3405	

Robust standard errors in parentheses

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

Table 8: The relationship between own follower success and the follower success of past adopters. Followers/Tweet (f_i) is an approximation based on the total number of followers divided by the total number of Twitter posts at the time of data collection.

	(1)		(2)		(3)		(4)	
	Followers/Tweet		Followers/Tweet		Followers/Tweet		Followers/Tweet	
Days to adopt	0.0524**	(0.0178)	0.0425*	(0.0174)	0.0401*	(0.0175)	0.0393*	(0.0181)
$(i-1)$	-0.148*	(0.0743)	-0.0452	(0.0593)	-1.209**	(0.375)	-0.370*	(0.183)
Month-time	0.204	(0.173)	0.0942	(0.154)	0.314	(0.182)	0.169	(0.161)
log(Population)	-5.404	(4.149)	-6.304	(3.972)	-4.827	(4.095)	-5.608	(3.932)
log(Income)	-7.138	(4.289)	-6.405	(4.112)	-7.734	(4.297)	-6.192	(3.954)
Percentage black	-0.179	(0.103)	-0.171	(0.100)	-0.194	(0.107)	-0.188	(0.103)
Gender	1.265	(2.813)	0.940	(2.814)	1.469	(2.893)	1.617	(2.987)
Black	8.659	(10.78)	8.410	(10.61)	7.227	(9.754)	8.485	(10.15)
Catholic	1.967	(2.953)	1.809	(2.860)	2.341	(2.954)	1.851	(2.836)
Law	-0.945	(2.557)	-0.668	(2.551)	-2.388	(2.576)	-1.328	(2.604)
Ivy	5.885	(5.705)	5.558	(5.655)	5.044	(5.089)	4.972	(5.366)
Age	0.162	(0.161)	0.0954	(0.157)	0.112	(0.150)	0.0768	(0.167)
Incumbent	-0.207	(3.108)	-0.675	(3.084)	-1.008	(3.086)	-0.754	(3.206)
Tenure	-0.108	(0.172)	-0.0869	(0.168)	0.0143	(0.154)	-0.0344	(0.157)
Democrat	0.828	(2.924)	-1.436	(3.122)	1.346	(2.882)	3.768	(8.017)
Bills	0.133	(0.155)	0.143	(0.152)	0.165	(0.148)	0.155	(0.154)
Chair	-3.649	(3.667)	-3.093	(3.779)	-5.052	(3.436)	-3.646	(3.688)
Number of committees	0.253	(1.100)	0.182	(1.090)	-0.312	(1.135)	-0.269	(1.143)
MySpace	20.79**	(7.345)	22.02**	(7.275)	21.03**	(6.662)	21.59**	(7.188)
RSS	0.0640	(2.901)	0.306	(2.901)	0.468	(2.762)	0.639	(2.910)
Flickr	-5.049*	(2.145)	-4.078	(2.071)	-3.442	(1.990)	-3.140	(1.963)
Facebook	-4.725	(4.336)	-4.910	(4.259)	-5.533	(4.172)	-5.971	(4.184)
Youtube	-0.290	(4.648)	0.728	(4.465)	-2.048	(4.450)	0.0344	(4.157)
f_{-i}	1.261***	(0.180)			1.414***	(0.166)		
$f_{-i,own}$			1.469***	(0.247)			1.589***	(0.259)
$f_{-i,other}$			0.888*	(0.352)			0.809**	(0.295)
$(i-1) * f_{-i}$					0.0920**	(0.0310)		
$(i-1) * f_{-i,own}$							0.00708	(0.0121)
$(i-1) * f_{-i,other}$							0.0199*	(0.00967)
Constant	108.9	(85.43)	97.08	(79.15)	94.85	(84.39)	79.10	(77.41)
Observations	183		183		183		183	
R^2	0.3005		0.3233		0.3459		0.3426	

Robust standard errors in parentheses

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

Table 9: Robustness of results. The first column controls for the order of entry, the second column controls for serial correlation, and the third column controls for sample selection using the 2-step Heckman method.

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
f_{-i}	-6.707***	(1.621)	-0.458*	(0.201)	-14.39***	(1.325)
$(i-1)$	3.117***	(0.153)				
Controls	Yes		Yes		Yes	
ρ			0.980			
λ					-141.7	(187.0)
Observations	183		182		438	
R^2	0.9302		0.1251			
Durbin-Watson statistic			0.432990			
Wald statistic					325.26	

Standard errors in parentheses

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

Table 10: Robustness of results. The first column controls for the order of entry, the second column controls for serial correlation, and the third column controls for sample selection using the 2-step Heckman method.

	(1)		(2)		(3)	
	Followers/Tweet		Followers/Tweet		Followers/Tweet	
f_{-i}	1.261***	(0.180)	0.481	(0.363)	1.065*	(0.470)
$(i-1)$	-0.148*	(0.0743)				
Controls	Yes		Yes		Yes	
ρ			-0.0756			
λ					50.94	(51.63)
Observations	183		182		438	
R^2	0.3005		0.1575			
Durbin-Watson statistic			2.062			
Wald statistic					107.30	

Standard errors in parentheses

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

Table 11: Robustness of results with respect to temporal events. The first column considers the subsample of adopters who did not adopt Twitter before and after the start of session (January 20, 2009) by 100 days. The second column considers the subsample of adopters $i > 50$.

	(1)		(2)	
	Days to adopt		Days to adopt	
f_{-i}	-14.98**	(4.766)	-108.9***	(11.97)
Controls	Yes		Yes	
Observations	95		133	
R^2	0.6472		0.7166	

Robust standard errors in parentheses

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

Table 12: Robustness of results with respect to temporal events. The first column considers the subsample of adopters who did not adopt Twitter before and after the start of session (January 20, 2009) by 100 days. The second column considers the subsample of adopters $i > 50$.

	(1)		(2)	
	Followers/Tweet		Followers/Tweet	
f_{-i}	1.004***	(0.251)	8.017*	(3.120)
Controls	Yes		Yes	
Observations	95		133	
R^2	0.3508		0.2817	

Robust standard errors in parentheses

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

Table 13: Robustness of results with respect to contextual effects. Note here that the average values are with respect to the past adopters.

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
f_{-i}	-14.68***	(4.155)	-7.909*	(3.471)	-6.917*	(3.259)
Average log(Population)	1745.5***	(151.1)	248.2	(193.3)	338.2	(278.5)
Average log(Income)	-2269.2***	(185.8)	-504.0*	(225.7)	-401.4	(336.1)
Average percentage black	36.93***	(7.865)	-12.11	(9.949)	-6.469	(8.932)
Average number of females			1207.5***	(328.9)	1391.9***	(290.9)
Average number of blacks			-615.7	(949.6)	-1404.7	(752.3)
Average number of catholics			-353.0	(264.3)	-384.6	(290.0)
Average number of law degree holders			-240.4	(161.9)	-143.8	(152.0)
Average number of Ivy league alumni			365.7	(201.7)	-346.3	(216.0)
Average age			31.88***	(8.325)	12.87	(9.115)
Average number of incumbents			-702.1**	(244.2)	-1904.3***	(292.3)
Average tenure			69.58***	(20.17)	115.3***	(19.10)
Average number of Democrats			1431.6***	(217.9)	1113.5***	(183.7)
Average number of bills			9.348	(7.821)	16.49*	(7.646)
Average number of chairs			-3135.5***	(323.3)	-2502.5***	(306.9)
Average number of committees			108.7	(133.8)	-205.3	(126.9)
Average number of MySpace users					-1506.5**	(570.2)
Average number of RSS users					-25.36	(109.1)
Average number of Flickr users					-72.41	(232.3)
Average number of Facebook users					1554.5***	(252.7)
Average number of Youtube users					-1258.9***	(214.6)
Constant	3218.9***	(696.7)	1252.0**	(451.4)	979.9*	(391.7)
Controls	Yes		Yes		Yes	
Observations	183		183		183	
R^2	0.8615		0.9701		0.9800	

Robust standard errors in parentheses

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

Table 14: Robustness of results with respect to contextual effects. Note here that the average values are with respect to the past adopters.

	(1)		(2)		(3)	
	Followers/Tweet		Followers/Tweet		Followers/Tweet	
f_{-i}	3.663*	(1.834)	3.856*	(1.851)	3.571*	(1.672)
Average log(Population)	41.70	(29.66)	37.69	(49.25)	122.2	(96.26)
Average log(Income)	-30.76	(40.30)	2.613	(58.19)	-129.5	(107.0)
Average percentage black	-0.393	(1.588)	0.959	(3.591)	-1.221	(4.020)
Average number of females			-46.15	(142.7)	-76.38	(143.5)
Average number of blacks			120.0	(341.2)	65.46	(336.2)
Average number of catholics			120.8	(73.86)	202.1*	(95.93)
Average number of law degree holders			-95.32	(56.32)	-39.43	(61.83)
Average number of Ivy league alumni			71.71	(92.44)	142.1	(125.0)
Average age			-3.362	(3.767)	-1.538	(3.455)
Average number of incumbents			-160.2	(103.5)	-131.3	(135.2)
Average tenure			-1.559	(8.408)	-1.049	(8.939)
Average number of Democrats			-123.2	(81.10)	-257.5*	(119.7)
Average number of bills			1.176	(1.694)	1.347	(1.847)
Average number of chairs			177.5	(245.3)	119.0	(227.2)
Average number of committees			-4.814	(70.41)	20.58	(72.73)
Average number of MySpace users					453.6	(285.2)
Average number of RSS users					4.991	(47.62)
Average number of Flickr users					158.2	(99.41)
Average number of Facebook users					-58.14	(104.8)
Average number of Youtube users					90.29	(104.1)
Constant	-115.0	(171.9)	-146.1	(203.1)	-115.7	(188.9)
Controls	Yes		Yes		Yes	
Observations	183		183		183	
R^2	0.3276		0.3809		0.4061	

Robust standard errors in parentheses

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

Table 15: Which information signals matter? The first specification (Column 1) defines f_{-i} to be the average followers/Tweet among the 10 most recent adopters prior to i, the second specification (Column 2) defines f_{-i} to be the average followers/Tweet among the 20 most recent adopters prior to i, and the third specification (Column 3) defines f_{-i} to be thea average followers/Tweet among the latter 10 (of the 20 most recent adopters).

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
f_{-i}	-14.75***	(2.982)	-17.51***	(4.136)	-6.619	(3.456)
Controls	Yes		Yes		Yes	
Observations	173		163		163	
R^2	0.3878		0.4007		0.3346	

Robust standard errors in parentheses

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

Table 16: Which information signals matter? The first specification (Column 1) defines f_{-i} to be the average followers/Tweet among the 10 most recent adopters prior to i, the second specification (Column 2) defines f_{-i} to be the average followers/Tweet among the 20 most recent adopters prior to i, and the third specification (Column 3) defines f_{-i} to be thea average followers/Tweet among the latter 10 (of the 20 most recent adopters).

	(1) Followers/Tweet		(2) Followers/Tweet		(3) Followers/Tweet	
f_{-i}	-0.519*	(0.250)	-0.617	(0.379)	-0.139	(0.186)
Controls	Yes		Yes		Yes	
Observations	173		163		163	
R^2	0.1819		0.2436		0.2344	

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 17: How adoption is affected by positive and/or negative surprises. A positive surprise for each individual i is defined as $1[(f_i - E(f_i)) > 0]$ and a negative surprise is defined as $1[(f_i - E(f_i)) < 0]$. The average contains all $-i$ who adopted prior to i.

	(1) Days to adopt		(2) Days to adopt		(3) Days to adopt	
Average number of positive surprises	-1054.0***	(59.31)			-1056.4***	(55.88)
Average number of negative surprises			28.07	(514.0)	116.7	(65.40)
Controls	Yes		Yes		Yes	
Observations	182		182		182	
R^2	0.7863		0.2865		0.7878	

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 18: Does geography matter? Here, $f_{-i,samestate}$ is defined as the average number of followers/Tweet among past adopters whose districts are in the same state as i, and $f_{-i,diffstate}$ is defined as the average number of followers/Tweet among past adopters whose districts are not in the same state as i.

	(1)		(2)		(3)	
	Days to adopt		Days to adopt		Days to adopt	
$f_{-i,samestate}$	-6.525***	(1.535)			-10.78***	(1.026)
$f_{-i,diffstate}$			-26.61***	(7.118)	-31.15***	(7.041)
Controls	Yes		Yes		Yes	
Observations	183		183		183	
R^2	0.3569		0.6021		0.7455	

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 19: Does geography matter? Here, $f_{-i,samestate}$ is defined as the average number of followers/Tweet among past adopters whose districts are in the same state as i, and $f_{-i,diffstate}$ is defined as the average number of followers/Tweet among past adopters whose districts are not in the same state as i.

	(1)		(2)		(3)	
	Followers/Tweet		Followers/Tweet		Followers/Tweet	
$f_{-i,samestate}$	1.009***	(0.132)			0.950***	(0.151)
$f_{-i,diffstate}$			-1.468	(0.774)	-0.223	(0.299)
Controls	Yes		Yes		Yes	
Observations	183		183		183	
R^2	0.3258		0.2294		0.3269	

Robust standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Figure 1: Twitter adoption over time.

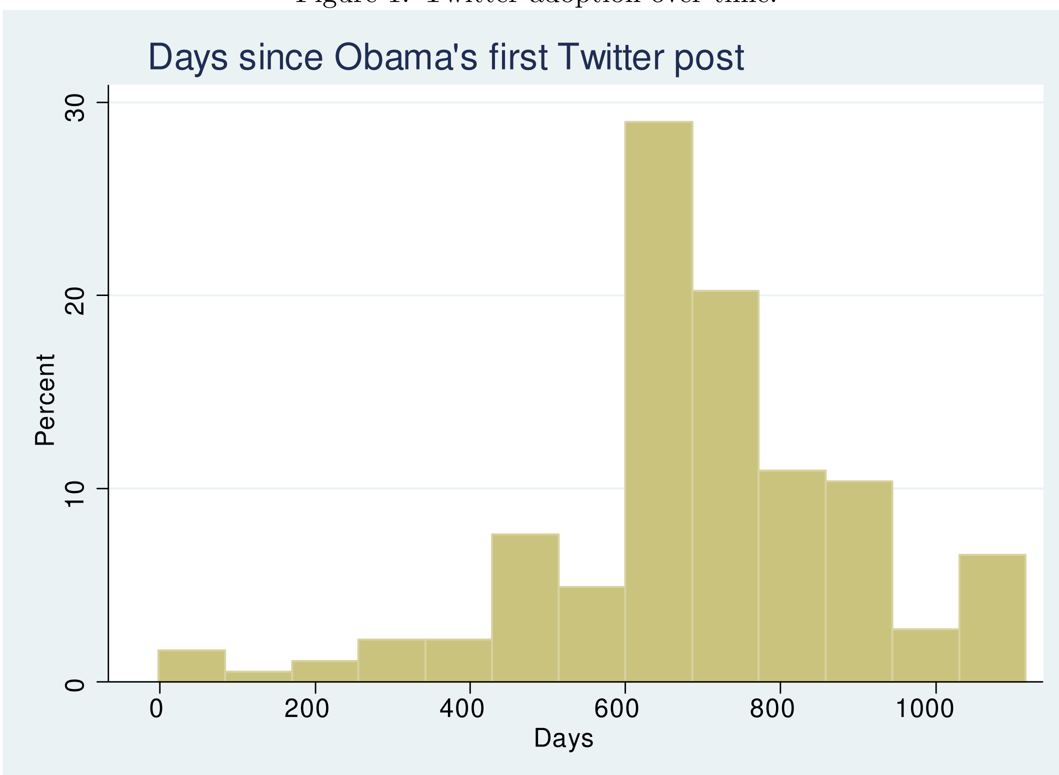

Figure 2: Correlation between followers/Tweet and month of adoption