Social Media and Political Donations: Evidence from Twitter*

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Abstract

Do new technologies change the way political markets operate in a democracy? We estimate the impact of adopting a new technology of political communication (i.e., opening a Twitter account) on political donations received by candidates running for the U.S. Congress. To identify the causal impact of joining Twitter, we compare donations before and after politicians open an account in regions with high and low levels of Twitter penetration. We estimate that opening a Twitter account amounts to an increase of 2-3% percent in donations per campaign, in a region with average Twitter penetration. This effect holds only for politicians who have never been elected to the Congress before. Using data from newspapers, blogs and documentation of campaign expenditures, we carry out a number of placebo checks to rule out alternate explanations for the increase in donations, testing for exogenous events coinciding with Twitter account opening. The gains from opening a Twitter account is stronger for donations coming from new as opposed to repeat donors and from regions with low newspaper circulation. Overall, our findings suggest that adopting a new technology, namely a social media channel, can lower the barriers to entry in political contests by increasing new politicians' opportunities of informing voters and fund-raising.

Keywords: social media, Twitter, political donations, elections, political candidates

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1 Introduction

In a democratic society, electoral competition and low barriers to entry in politics promote good economic policies and reduce corruption [e.g., Besley et al., 2010, Ferraz and Finan, 2011, Galasso and Nannicini, 2011, Myerson, 1993, Persson et al., 2003]. Barriers to entry in politics and the associated incumbency advantage emerge because challengers don't have enough opportunities to communicate with voters, which limits fund raising activities as well as awareness about their ability and policy positions[Prat, 2002, Prior, 2006, Ansolabehere et al., 2000, Strömberg, 2004]. The persistent advantage enjoyed by experienced politicians is one of the best-documented electoral outcomes in the United States. Incumbents are reported to achieve re-election rates of over 90% [Levitt and Wolfram, 1997]. They also receive higher levels of media coverage and endorsements, creating barriers to entry for new politicians. New communication channels such as Twitter allow politicians to access an alternate, relatively cost-effective channel to inform voters about their policies and raise campaign funds, potentially reducing the incumbency advantage in electoral races. Whether using Twitter actually helps to increase the amount of political donations received, especially for the new candidates, is an open question.

In this paper, we study the consequences of politicians' adoption of a new communication technology (namely, opening a Twitter account) on the campaign contributions received while running for the U.S. Congress. Using data from Twitter, we evaluate if adopting Twitter helps politicians to inform voters and consequentially increase the financial support received from them. Put differently, we test if the contributions politicians receive from constituents change before and after joining Twitter, comparing regions with low and high Twitter penetration. We use data which includes 1814 politicians who opened a personal Twitter account between 2009 and 2014, their campaign contributions from Federal Election Commission (FEC), and how Twitter use compares to other sites in the politician's region (i.e., Twitter penetration) information from the comScore online browsing panel.

The findings from our analysis suggest that adopting Twitter helps politicians to increase the contributions received. Weekly aggregate contributions received increases after a politician opens an account on Twitter. However, strikingly, this gain holds for the new politicians who have never been elected to Congress before, but not for the experienced ones who have. The aggregate political donations of the average new politician increase by a minimum of $5773, and on average they see an increase corresponding to 2.3% of all donations under $3000 per contribution raised during the campaign. The increase in aggregate donations come from new donors (i.e., those who never donated to the politician before) but not from repeat donors. This suggests that politicians may increase awareness about themselves and their policies via Twitter and gain support from those who did not support them before. An analysis of the Tweet content strengthens this hypothesis. Additional tests demonstrate that the gains from Twitter are higher for the politicians who come from low newspaper circulation areas. Overall, these findings suggest that political contributions respond to politicians' adoption of Twitter. The informational gains from this new communication technology can benefit voters and therefore, estimating the magnitude of this effect is of relevance to policy makers. A broader implication of our study is that adoption of Twitter may reduce the gap in fund-raising opportunities between new and experienced politicians, which, in turn, helps to lower the barriers to winning political contests.

Identifying the causal impact of Twitter on political donations is not trivial, chiefly because there can be a host of correlated unobservables which influence both the politician's decision to join Twitter and the amount of political donations raised. Our estimation uses a difference-in-differences strategy to compare donations a politician received before and after joining Twitter, in regions with low and high Twitter penetration. We control for politician-month fixed effects to account for politician-specific unobserved characteristics, such as being more progressive-minded, more tech-savvy, or being at a different stage of campaigning. Our identifying assumption is that the differences between contribution flows, unexplained by politician-month fixed characteristics, would be the same in the absence of Twitter entry in areas where Twitter has low and high penetration. Put differently, we rely on a parallel trends assumption, but our identification does not assume that politicians' decision to join Twitter is random or exogenous to their fund-raising.

We use a number of placebo tests to ensure that this identifying assumption is plausible. First, we show that there is no discontinuous increase in campaign spending around the time of Twitter entry, across high and low Twitter penetration areas, despite the fact that political donations are closely related to campaign spending in a given week. Second, to control for possible exogenous events which may coincide with Twitter entry and a discontinuity in funds raised, we show that the media coverage of the politicians does not show a significant change around the time of Twitter entry, again that there are no differences between the high and low Twitter penetration areas. Third, we check that Twitter entry does not differentially affect contribution patterns in places with different income, education, political preferences, and racial composition, therefore it is unlikely that Twitter penetration is just a proxy for one of those variables. Overall, while we cannot test the parallel trends assumption directly, the results in all our placebo specifications are consistent with it.

Our study contributes to several streams of literature. First, we complement the literature which documents the positive impact associated with political competition and lowering barriers for entering politics on good governance and welfare [Besley et al., 2010, Ferraz and Finan, 2011, Galasso and Nannicini, 2011, Myerson, 1993, Persson et al., 2003]. Besley et al. [2010]show that low political competition leads to low economic growth while Galasso and Nannicini [2011] show that electoral competition is good for political selection. Closely related, Ansolabehere et al. [2000] as well as Prat [2002], Prior [2006] study different sources of incumbency advantage, listing the lack of information of voters about the new candidates and lack of funding opportunities. Our paper relates to this stream by empirically highlighting how the advent of social media in general, and Twitter in particular, can potentially intensify political competition by improving opportunities of new candidates to raise funds and inform voters in a cost-effective fashion.

Next, we contribute to the literature that studies the role of campaign contributions in political processes. Grossman and Helpman [2001, 1996] argue that campaign contributions allow special interest groups to influence policy outcomes. Similarly, theoretical literature on campaign finance regulation and campaign contribution limits is primarily focused on instrumental motivation for contributions [Coate, 2004, Ashworth, 2006, Drazen et al., 2007, Cotton, 2009, 2012, Prat, 2002, Chamon and Kaplan, 2013]. In all these models, campaign contribution limits have different implications depending on whether advertising spending reveal some information about the types of politicians [Prat, 2002, Cotton, 2012, Coate, 2004] or enhance incumbency advantage [Ashworth, 2006]. Prat et al. [2010] estimate information benefits from private campaign advertising and find that they are small. Our paper contributes to this literature by highlighting that activity on Twitter can actually raise donations for inexperienced candidates by providing new information about the politicians.

We also contribute to the emerging literature on the impact of social media on various socioeconomic outcomes. Shiyang Gong and Jiang [2015] and Seiler et al. [2016] study the impact of advertising of TV content in Chinese micro blogs on subsequent TV series viewership. Acemoglu et al. [2014] and Enikolopov et al. [2016] look at the impact of social media content and penetration on subsequent protest participation. Qin et al. [2016] study the content and the impact of social media in China for collective action outcomes, while Qin et al. [2013] looks at the relationship between Twitter penetration on drug quality. In contrast to this literature, we focus our investigation on the strategic benefit of entry into an online social network for the politicians, quantifying their financial gain, and investigating information mechanisms behind the impact of this entry in detail.

Lastly, our paper is also related to literature on the impact of information and communication technologies (ICTs) and traditional media on political preferences and policy outcomes. Recent papers have shown that traditional media has an impact on voting behavior [DellaVigna and Kaplan, 2007, Enikolopov et al., 2011, Gentzkow et al., 2011, 2014, Chiang and Knight, 2011], violence and ethnic tensions [Yanagizawa-Drott, 2014, Vigna et al., 2014, Adena et al., 2014], women's status and fertility [Jensen and Oster, 2009, La Ferrara et al., 2012], or policy outcomes [Strömberg, 2004, Strömberg Jr and Snyder Jr, 2008, Eisensee and Strömberg, 2007]. We complement this stream of the literature by highlighting a mechanism through which ICTs could influence political outcomes-by providing an efficient channel to raise political donations. A number of earlier studies point to the challenges of measuring the benefits from social media [Bollinger et al., 2013, Culotta and Cutler, 2016, Ma et al., 2015, Lovett and Staelin, 2012]. Our findings suggest concretely that these platforms can generate positive returns.

2 Data

Our study uses data from a variety of sources. We compile a list of politicians available from the Federal Election Commission (FEC) which includes those who either registered with the FEC or whose name is mentioned on the state ballot for an election to the U.S Senate or House of Representatives from 2009 to 2014. For each politician, we combine weekly data on campaign contributions with data on their Twitter activity. We also acquire information on the campaign expenditures and the number of media mentions on Google News and Google Blogs of each candidate. Finally, we gather data about how Twitter usage compares to the usage of other websites in each US state, using data from the company comScore. Summary statistics for the different variables are provided in Tables 1 and 2.

Campaign Contributions and Expenditures

The main data source for political donations for our study is the Federal Elections Committee (FEC), which makes data on campaign contributions for each candidate publicly available. Our data focuses on the contributions to candidates, rather than to PACs or other organizations. In most parts of the analysis, we limit the analysis to donations under $1000. The data details the amount of each contribution, its date and the name of the donor. For this sample, the average amount of donations per week for a politician is $516 and the median amount is $500 . We use donations aggregated at the politician-week level.

The source of data for the campaign expenses is the Center for Responsive Politics (opensecrets.org). The site lists the exact date for each piece of expenditure made by each candidate, and we use the aggregated weekly campaign expenses of the candidate as a variable in our analysis.

Twitter Account Opening

For each politician in our list, we collect information on their Twitter activity.[1] We use an automated script to gather information about whether a politician has Twitter account or not and if there is one, we collect a variety of data related to it. We identify the date that the account was first activated and supplement it by information on the number of tweets, re-tweets, the text of all the tweets as well as the number of followers.

Figure 1 demonstrates the distribution of the date of Twitter account opening for the politicians between 2009 and 2014. The distribution shows that entry on Twitter takes place continuously between 2009 and 2014. This variation in entry dates reduces the concern that politicians' entry may correlate with the timing of a few specific events. To further reduce the concern that

[1] A detailed description of the data collection process is given in the Data Appendix.

donations are influenced by other campaign activities than Twitter account opening, we drop any Twitter account which has "2010", "2012", "2014" or "4" (e.g., "@chip4congress", "@MCarey2012") in the handle string which may indicate that it was started for an upcoming campaign.

Twitter Penetration

We collect information about the use of Twitter relative to other sites by the general population in the U.S. by creating a penetration measure. We construct this metric by using data from comScore internet browsing data. The dataset provides a panel of fifty thousand households who have been tracked in their online activities throughout the period of data collection. Each household's browsing activities are tracked through a machine and all browsing of websites is recorded. This allows us to create a measure of engagement with Twitter relative to all sites, which we refer to as Twitter penetration which is aggregated at the state-year level. Formally:

$$\text{Twitter Penetration} = \frac{\text{Number of Site Visits to Twitter}}{\text{Number of Visits to All Websites}}$$

Twitter penetration plays a significant role in our identification strategy which we will detail subsequently. Note that, we normalize Twitter penetration so that mean penetration is equal to 1 (with the median penetration being 0.99 - close to the mean of the distribution).

News and Blogging Data

For each politician on our list, we collect information on the number of media mentions for a window of ten weeks before and after they started using Twitter. We run a search for the number of times his or her name has appeared in Google News and Google Blogs. We use this information to check whether there are systematically more media mentions of a politician around the time her Twitter account is started. If there are various other events related to a politician's campaign which could affect the amount of donations generated then the number of media mentions could capture it and prove to be a useful robustness exercise.

Politician Data

We collect additional data about the politicians using two different data sources. The first source is FEC, and the second is VoteSmart database, which provides information about their age, education, income, and voting history.

Throughout the empirical section, we extensively use the division of politicians into 'new' ones and 'experienced' ones. A politician is 'new' if she was never been elected to Congress before. If the politician has already won an election in the past, then she is classified as 'experienced'. We also use the more traditional classification of incumbents and challengers. Note that a challenger could be an experienced politician if she was elected before.

Other variables

Finally, we also use data on demographics at the state level such as household income, share of rich (i.e. share of households with over 250K income), share with college education, and share of African-American population from Census, aggregated at the state level. We use data on newspaper circulation per capita from the American Association of Newspapers. We also use data on the vote share received by George W. Bush in 2004 Presidential elections from uselectionatlas.org.

We also collected data on dates of the first public post on Facebook for all the politicians in our list. We then create a dummy variable equal to one if a politician had opened a Facebook account before joining Twitter, and zero otherwise (i.e. for politicians with a Twitter account).

3 Background

Use of Social Media by Politicians

Until recently, traditional media held the role of being the primary information channel for politicians, so obtaining coverage on newspapers and TV outlets became crucial for electoral success. Candidates further engaged in dissemination of information about their candidacy and policy goals by the speeches they give along the campaign trail and through public appearances [Garcia-Jimeno and Yildirim, 2015]. Today, a reported 80% of the politicians around the world use Twitter to communicate with their constituency[2]. The content of this communication is more personal compared to the regular campaign messages and includes information about politicians' lives and activities outside of politics. While politicians who are well known and hold high political positions typically reach out to several million followers on Twitter, lesser known politicians communicate with several thousand individuals. Barack Obama, for instance in 2016 had over twenty-three million followers while Mike Pence, Orin Hatch and Jared Polis had over thirty thousand accounts following them. According to our data, the number of Congressional candidates, who use Twitter, changes from 741 in 2009 to 1,024 in 2010 to 1,488 in 2012 to 1,814 in 2014.

After the 2008 election, scholars predicted increased and targeted web use by political campaigns at the federal and local level [Towner and Dulio, 2012]. This included use of Social Networking Services (SNSs), which allow candidates to build profiles and showcase connections within a delimited system [Boyd and Marwick, 2011, Boyd and Ellison, 2012]. Among these sites, Twitter

[2] http://www.adweek.com/socialtimes/world-leaders-twitter/495103

is unique due to its confinement to 140-character messages and the lack of restrictions on viewing messages in the form of account-owner permissions. Followers are said to establish connections for the content, rather than the relationships, resulting in numerous ties that span physical and social disparities [Virk et al., 2011]. Twitter brings with it new possibilities for candidate-voter interaction as the “@username” function allows candidates to reply directly to other users and promote dialogue. Managing a Twitter audience, therefore, requires constant activity to respond to, monitor, and understand audience interests [Boyd and Marwick, 2011]. It is not surprising that this platform is fraught with potential communication challenges. These challenges include an absence of authoritative hierarchies [Metzgar and Maruggi, 2009], the possible loss of message control [Gueorguieva, 2008, Johnson and Perlmutter, 2010] and overall blurring of traditional audience conceptualizations [Marwick et al., 2011]. Scholars and pundits also question whether the overall use of SNSs by politicians actually matters when it comes to voting outcomes [Kushin and Yamamoto, 2010, Baumgartner and Morris, 2010, Zhang et al., 2010]. Although the number of Twitter users continues to increase, only a fraction of those users report using the site to gather political information [Smith, 2011, Smith and Rainie, 2008]. Right now, Twitter and other SNSs are still seen as complementary to traditional outreach mediums [Towner and Dulio, 2012]. The true payback may be in organizing volunteers and activists, an aspect some maintain is overlooked [Abroms and Craig Lefebvre, 2009]. The primary benefits of the SNS as a campaign tool are said to include low cost, enhanced recruitment of volunteers and contributions, and a space for lesser known candidates [Gueorguieva, 2008]. One benefit of all social media is the direct and unrestrained nature of the communication which allows candidates to bypass traditional media outlets [Lassen and Brown, 2010].

There are a number of studies on how social media influences campaigns using correlational evidence. Metaxas and Eni [2012], for example, comment on the relationship between social media use and elections from the perspective of predicting electoral outcomes, while Hong and Nadler [2011] demonstrate how the use of Twitter correlates with the shifts in polls during election periods. From the perspective of politicians, policy makers as well as consumers of social media, documenting a robust causal impact of the different mechanisms at play is essential to the understanding of the role played by social media in the electoral process.

Media and Incumbency Advantage

Incumbency advantage is one among the best-documented electoral patterns in the United States [Ansolabehere et al., 2006a]. Starting with a 1-2% point advantage in the 1940s, incumbents reportedly enjoyed increasing levels of electoral wins, reaching about 8-10% during the 2000s. A rich literature offers explanations for why known and incumbent politicians with experience enjoy this advantage in elections. Higher chances of re-election may simply stem from differences in quality of the candidates. Some of these politicians may simply be more skilled than their opponents [Jacobson and Kernell, 1982] and hence enjoy higher chances of re-election. But, the incumbency advantage can also be due to the opportunity the incumbents enjoy to use staff and committee positions to raise campaign funds [Cox and Katz, 1996].

Another advantage incumbents hold is the disproportionate attention they receive from the media. During elections, traditional media acts at the primary source for voters not only for conveying basic information about the candidates but also for influencing the decisions of the voters through endorsements. A number of scholarly works suggest that the coverage of a candidate as well as whom the media embraces, influences public's decision to support a candidate. Survey-based findings suggest that incumbents enjoy higher levels of media coverage [Ansolabehere et al., 2006a, Clarke and Evans, 1983, Goldenberg and Traugott, 1980]. Ansolabehere et al. [2006b] find that endorsements influence the outcome of an election by about 1-5% points. Traditional media such as TV and newspapers are devoted to supporting the better known politicians, and voters are more likely to support candidates who they can recognize [Jacobsen, 1987]. These findings suggest that experience in politics - both through higher public recognition and through holding a public office - can put new politicians at a disadvantage, and discourage their entry into political contests [Cox and Katz, 1996]which in turn, reduces the competitiveness of electoral races. Less competitive races will make politicians feel lower levels of responsibility and accountability towards their constituents [Carson et al., 2007]. These concerns together suggest that new technologies which can reduce the incumbency advantage can help elections to be contested on fairer grounds.

4 A Simple Model of Political Donations

We sketch out a simple partial equilibrium framework of donation decisions by potential political donors. We analyze donation decisions in situations where politicians do and do not use Twitter. In this framework, we abstract away from explicitly modeling the strategic decision of politicians to join Twitter. We use the model to derive some testable predictions on donation decisions which we then take to the data.

The Framework

Consider a setting where politicians can be either new or experienced, indexed by $i \in \{e, n\}$. A politician i has a 'type' or quality, $\theta_i \in [0, 1]$ interval. The politician knows her θ_i. There is a unit mass of potential donors. We assume that all potential donors want a higher 'quality' politician which, in this context, can be interpreted as the honesty or experience of the politician.[3]

[3]Analyzing quality instead of ideology is more pertinent in our context, since we analyze donations within states, where ideological differentiation within a party would be limited. In such a situation, information via Twitter is more likely going to be about their integrity, experience and track record. This modeling choice is in line with Durante and Knight (2012) as well as Knight and Chiang (2011).

We adopt a (linear) separable utility framework for donors similar to Knight and Chiang (2011) and Matjeka and Tabellini (2015). An individual donor d has the following utility from donating to politician i:[4]

$$U_{di} = \theta_i - c_d$$

The term $c_d \sim U[0,1]$ captures the cost of donating which affects each donor idiosyncratically. We normalize the outside option of the donors to 0. The donors do not observe θ_i but hold (unbiased) prior beliefs such that

$$\theta_i \sim N(\bar{\theta}_i, \sigma_{i0}^2)$$

We assume that $\bar{\theta}_e > \bar{\theta}_n$ which will imply that ex-ante, without Twitter, experienced politicians have an advantage in terms of getting higher donations relative to newer politicians. We will focus on the case where $\sigma_{n0}^2 > \sigma_{e0}^2$. The higher variance for new politicians implies that ex-ante, the donors place less confidence in their estimate of θ_n relative to θ_e. This structure is in line with the evidence that experienced politicians hold an informational advantage over newer candidates as exhibited in Anderson (2004) and Oliver and Ha (2007).

If a politician does join Twitter then she can provide information to the donors or could involve (rational or non-rational) persuasion similar to advertising messages. The politician can send a message m to the voters such that:

$$m_i = \bar{\theta}_i + \epsilon_i$$

with $\epsilon_i \sim N(0, \sigma_{i\epsilon}^2)$.

The Donation Decision

To highlight how joining Twitter affects donations differentially for new and experienced politicians, we analyze the donations received by each type of politician with and without Twitter. If the politician does not join Twitter, donor d will donate if

$$E(\theta_i) \geq c_d$$

Normalizing each donation to 1, the total amount of donations is then given by $\bar{\theta}_i$ since $E(\theta_i) =$

[4]The linear utility framework is exactly in line with Knight and Chiang (2011) and Durante and Knight (2012). Matjeka and Tabellini (2015) adopt a more general framework where $u(\theta_i)$ is concave and differentiable. Our main insight would hold in such a setting as well (with a bit more algebra as in Matjeka and Tabellini (2015)) as well other frameworks such where voters have a bi-modal policy preferences.

$\bar{\theta}_i$. If a politician does join Twitter then she will send a message m_i which will be used by the donors to update their beliefs about θ_i. The posterior belief after seeing m_i is:

$$E(\theta_i|m_i) = V_i m_i$$

where $V_i = \left(\frac{\sigma_{i0}^2}{\sigma_{i0}^2+\sigma_{i\epsilon}^2}\right)$. If a politician does join Twitter, donor d will donate if

$$E(\theta_i|m_i) \geq c_d$$

and then the amount of donations received is $E(\theta_i|m_i)$. We define $\Delta_i \equiv E(\theta_i|m_i) - E(\theta_i)$. If $\Delta_i > 0, \forall i$ then we can establish the following:

Proposition 1. *A new politician gains more from joining Twitter relative to a more experienced one:*

(1) The higher σ_{n0}^2 is relative to σ_{e0}^2, which implies $\frac{\partial(\Delta_n - \Delta_e)}{\partial(\sigma_{n0}^2 - \sigma_{e0}^2)} \geq 0$.

(2) The higher $\sigma_{e\epsilon}^2$ is relative to $\sigma_{n\epsilon}^2$, which implies $\frac{\partial(\Delta_n - \Delta_e)}{\partial(\sigma_{e\epsilon}^2 - \sigma_{n\epsilon}^2)} \geq 0$.

Proof. The proof follows straight from writing out the expressions for Δ_i. $E(\theta_i|m_i) - E(\theta_i)$ is simply $\left(\frac{\sigma_{i0}^2}{\sigma_{i0}^2+\sigma_{i\epsilon}^2}\right)(\bar{\theta}_i + \epsilon_i) - \bar{\theta}_i$. This implies that $\Delta_n - \Delta_e = (V_n - 1)\bar{\theta}_n - (V_e - 1)\bar{\theta}_e + V_n\epsilon_n - V_e\epsilon_e$. The comparative statics in the proposition follow directly. **QED**

The proposition implies new politicians see a bigger increase in political donations from joining Twitter relative to experienced politicians, the larger σ_{n0}^2 is relative to σ_{e0}^2. The condition $\Delta_n \geq \Delta_e$ is also likely to hold if the messages sent by new politicians have higher precision: $\sigma_{e\epsilon}^2 \geq \sigma_{n\epsilon}^2$. More generally, if the use of Twitter by new politicians is more informative than the experienced ones then they will benefit more from using the platform.

Donations and Twitter Penetration

Till now, we have assumed that there is universal access to Twitter and all donors observe how informative the use of Twitter is for all politicians. As in our empirical model, we assume that there are different geographical regions (states), $s \in \{1, 2, ..., S\}$ with different twitter usage. Each state has a unit mass of potential donors. Moreover, we assume that only a (random) fraction ϕ_s uses Twitter. This assumption is in line with Butters (1977). This penetration coefficient varies across states with $\phi_1 \geq \phi_2 \geq .... \geq \phi_S$.

Assuming that Twitter penetration is the only dimension which varies across regions, we can easily see that politicians in regions with a higher ϕ_s will receive a bigger increase in donations by joining Twitter:

$$\phi_s \Delta_i \leq \phi_{s-1} \Delta_i$$

This also shows that if $\phi_s = 0$ for some s then in that region there will be an insignificant increase in donations for both experienced and new politicians.

5 The Empirical Framework

5.1 Empirical Hypotheses

Based on the simple framework highlighted in the model, a number of hypotheses can be derived.

(1) Politicians, on average, can potentially increase their donations by joining Twitter since it serves as an additional channel of communication.

(2) The gain for new politicians from joining Twitter will be higher relative to more experienced ones due to being relatively unknown initially.

(3) Regions with higher Twitter penetration will contribute more political donations with politicians joining Twitter.

Our main empirical hypothesis is that politicians who join Twitter gain access to an additional, relatively inexpensive channel of communication with their electorate. As a result, several things could happen. First, Twitter might help to provide new information to the members of politician's constituency. This information channel is more likely to hold for new politicians. Second, Twitter could allow politicians to engage in non-rational persuasion, potentially through repeated interactions through political messages which is more likely to hold for more experienced politicians who have greater access to their potential donors across different media platforms. In all these cases, we expect Twitter to affect the behavior of potential donors in a positive way. To investigate potential channels, we also check whether this hypothesis holds for new politicians, new donors, and in less saturated information environments.

Figure 2 demonstrates how political donations change in high-Twitter penetration and low-Twitter penetration places, controlling for basic set of fixed effects (politician and week fixed effects), before and after Twitter entry. There are two takeaway points from this figure. First, donations increase after joining Twitter, but not before, and this effect is stronger in places with high Twitter penetration. Second, there were no significant pre-trends in the difference between high- and low- Twitter penetration places before joining Twitter. Overall, Figure 2 illustrates our main point: the entry to Twitter helps politicians to raise political donations, and more so in high Twitter penetration places.

5.2 Main Specification

To study how opening a Twitter account influences the amount of political donations received, we use a difference-in-differences approach exploiting the precise timing of entry on Twitter. The main specification we estimate is:

$$DonationOutcome_{it} = \alpha_{im} + \theta_1 Entry_{it} + \theta_2 Entry_{it} \times Penet_{sy} + \theta_3 Entry_{it} \times \mathbf{X_s} + \theta_4 log\left(Expenditures_{it}\right) + \theta_5 t + \epsilon_{it} \tag{1}$$

where i is the index for politicians, t is a week level time index, s is the index for state. $DonationOutcome_{it}$ will represent various ways of measuring donations received by politician i in week t, such as the log of aggregate dollar value of donations and the probability of receiving at least one donation. $Entry_{it}$ is a binary variable =1 if politician i has a Twitter account in week t and 0 otherwise. $Penet_{sy}$ is the level of Twitter penetration or usage in each state s which we aggregate at the annual level (and hence the subscript y). α_{im} is a politician-month fixed effect. $\mathbf{X_s}$ is a set of controls including average education in state, median income, percent rich (i.e., households with annual income of over $250,000 or more), percent voting for Bush in the 2004 elections, and race (percentage of the African-Americans). $Expenditures_{it}$ is campaign expenditures by politician i during week t. We do not include direct effect of $Penet_{sy}$ as it is perfectly collinear with politician-month fixed effects.

We allow for flexible controls in our specifications with politician-month fixed effects. Politician-month fixed effects account for unobserved differences in a politician's ability to attract donations and we control for this by allowing this ability to fluctuate temporally from month to month. Note that, our baseline results practically remain unchanged if we replace linear time trend with week fixed effects. We cluster standard errors at the level of the state, to account for both cross-sectional and time-series variation.

Our main coefficient of interest is θ_2, corresponding to the interaction between entry on Twitter and penetration. If Twitter indeed allows politicians to share new information with the members of constituency, we expect this coefficient to be positive and significant.

We do not claim that the decision to join Twitter is exogenous or taken completely at random, since this decision could be driven by a host of factors which we cannot fully observe. Our identification rather assumes parallel trends, i.e., that the difference in political donations, unexplained by politician-month fixed effects, would remain the same in the absence of Twitter entry across areas of high and low Twitter penetration.

We use a variety of placebo checks to check the credibility to this identifying assumption. One potential issue with our identification strategy might be that there could be other events happening simultaneously which would drive both the Twitter entry in areas of high and low penetration as well as donations to the politicians. If this is true and the politician is involved in multiple campaign activities, this is likely to reflect on the campaign expenses reported to FEC. We test whether campaign expenditures show a spike around the time of opening a Twitter account. We use the mandatory campaign expenditure data disclosed to FEC by the candidate. These expenditures may relate to activities on the campaign trail such as visits to towns, or a TV or newspaper advertisement purchase.

As another check to test for other events which may coincide with adopting Twitter, we look at the coverage of politicians in the news media. Any report or feature of the candidate by the traditional media coinciding with the opening of a Twitter may influence donations. Similarly, if instead of explicit features in the news, there were external events which gave a boost to the candidate's donations, they are likely to be captured in the media that week. Using data collected from Google News and Google Blogs, we test whether the number of articles or the blogs which mention a candidate increase discontinuously around the time of opening an account.

Our identifying assumption would also be violated if the characteristics of the regions which makes individuals spend a higher proportion of their online visits also correlated with their tendency to donate. To check for any systematic differences, we regress aggregate donations on a set of demographic characteristics included in $\mathbf{X}$, interacted with a dummy for being on Twitter.

6 Baseline Results, Placebos and Mechanisms

6.1 Baseline Results

We begin our analysis with the main specification given in Equation (1) to evaluate the impact of joining Twitter on the aggregate weekly political donations received. The main independent variable of interested is the politician's presence on Twitter interacted with Twitter penetration. The results of the estimation are presented in Table 3, with several sets of controls included in the estimation. As one can see from this table, our main coefficient of interest, having an account on Twitter interacted with Twitter penetration, is positive and significant in the specification which includes politician-month fixed effects (columns (2)-(5)). The coefficient remains stable in magnitude (0.378). The direct effect of being on Twitter disappears once a week time trend is introduced (column 4). This means that in areas with no Twitter penetration, joining Twitter alone is not associated with an increase in donations. Columns (6) and (7) estimate equation (1) separately for the sub-samples of new and experienced politicians. Column (6) suggests that joining Twitter was especially helpful for new politicians. However, we do not find any significant impact of joining Twitter on donations for experienced politicians (column (7)) even in areas of higher Twitter usage, consistent with the information mechanism. The increase for the lesser known, new politicians is larger and economically meaningful, since these politicians typically are at an informational disadvantage compared to the experienced politicians.

We do some back of the envelope calculations to interpret the magnitudes in our regressions. We include both the campaign and non-campaign periods in our estimation, and the average donation per candidate per week is \$1,534 per week and the average length of time being on Twitter after joining till the end of the month is 2.79 weeks (note that once the month is over, the coefficient that indicates being on Twitter for a politician becomes perfectly colinear with politician-month fixed effect). Using our coefficient, the back of the envelope calculation yields

$1,534 × 0.378 × 2.79= $1,618. Here we make the calculations for an average politician in a place with mean Twitter penetration (which is normalized to 1). Note that this number ($1,618) is likely to be an underestimation of the effect o Twitter on aggregate funds, as Twitter is likely to continue to help politicians receive donations even after the first month of adoption. Similarly, for new politicians, a similar number is obtained by multiplying $1,077 (average donation per week) with 0.69 (the coefficient from column 6) and with 2.79 weeks, which yields $2,078. Overall, these results suggest that adopting a new communication channel by joining Twitter leads to an average increase of 1.6% (for all politicians) or 2.6% (for new politicians) of the total donations below $1,000 raised over a two year campaign period.

Figure 3 shows how our coefficient of interest (interaction of being on Twitter with Twitter penetration) changes before and after joining Twitter. There do not seem to be any pre-trends in our coefficient of interest, as all leads of this coefficient are insignificant, with two out of three leads being negative. In contrast, the coefficients for Twitter entry interaction become positive and significant after a politician joins Twitter.[5] The main takeaway from this picture is the absence of significant pre-trends in our coefficient of interest, consistent with graphical illustration in Figure 2.

The results in Table 3 suggest that politicians are able to raise more money after joining Twitter. Table 4 tests whether similar results hold at the extensive margin, i.e., whether politicians are likely to receive higher number of donations in a given week after joining Twitter. The results in Table 4 suggest that joining Twitter helps to raise donations in every week. In terms of the magnitudes, the probability of at least one donation per week increases by 5.1 percentage points for all politicians, and for 8.4 percentage points for new politicians. The results for old politicians remain insignificant, consistent with the results in Table 3.

Finally, we also check whether the results for donations hold for different donation sizes. We estimate equation (1) for donations between $1,000 and $3,000. We report the results for both aggregate donations and for the probability of at least one donation in a given category. Table 5 summarizes these results. We find that while there is no average effect of joining Twitter for the sample of all politicians, there is still an impact of joining Twitter for the sample of new, inexperienced politicians (column 3). The size of the interaction coefficient (0.57) is smaller than the size of interaction coefficient for donations below $1,000 (Table 3). In terms of absolute dollars, however, the impact seems to be stronger, as these are larger donations. The average weekly sum of donations from a given category is $2,313. After multiplying $2,313 by 0.57 by 2.79, as in the calculations above, we find that Twitter can explain at least $3695 extra from donations between $1,000 and $3,000. This constitutes 2.1% of total donations to an average politician in a given category. Similarly, columns (5)-(8) report the results for extensive margin. For an average politician, the probability of receiving at least one donation between $1,000 and

[5] The week-by week coefficients are noisy, and the original regression includes politician-month fixed effects, so the coefficients for individual weeks should not be taken as the estimates of time-variant persuasion curve over time.

$3,000 goes up by 3.3 percentage points, while a similar probability for a new politician goes up by 6.7 percentage points. Thus, the results for the extensive margin are smaller in magnitude than similar results for donations below $1,000.

We demonstrate the robustness of our findings by testing different specifications. Varying the window size in the difference-in-differences specification does not alter the estimate of the interaction between being on Twitter and Twitter penetration in Table 13 in the Appendix. When we vary the window size for our diff-in-diff specification from ± 5, ± 10 weeks to up to ± 300 weeks, our aggregate estimates stay highly stable at 0.37 and significant at the 5% level throughout. Estimating our main specification for donation values greater than $3000 does not show a significant effect of Twitter.[6] This is expected, since donors who make large contributions may have different reasons to contribute than the ordinary citizens and are less likely to be influenced by the regular Twitter communication.

Overall, the results in Tables 3, 5 and in Figures 2 and **??** suggest that joining Twitter allows the politicians to raise a larger dollar sum of donations, but only for new politicians.

6.2 Plausibility checks

Our identifying assumption is that the difference in political donations, unexplained by politician-month fixed effects, would remain the same in the absence of Twitter entry across areas of high and low Twitter penetration. While we cannot test this directly, we conduct several tests to ensure that the data is indeed consistent with our identifying assumption.

6.2.1 Campaign Expenditures

A first potential threat to identification is the possibility of a correlation between the timing of Twitter entry and other campaign activities. While we do not have detailed measures of campaign activities, we use campaign spending per week as a proxy for campaign activities which may involve raising funds. The estimates in Table 3 show that weekly campaign expenditures are significantly correlated with campaign contributions, indicating that this measure is indeed meaningful. To check for potential simultaneous changes in campaign activities, we test if there is a spike in campaign expenditures around the date politicians start using Twitter. Table 6 shows that controlling for politician-month fixed effects and including a week time trend, joining Twitter does not predict an increase in the campaign expenditures neither in high nor in low Twitter penetration areas. Both the direct and the interaction terms are insignificant for the full sample (column (4)) in explaining campaign expenditures. This result also holds separately for both new (column (5)) and more experienced politicians (column (6)). To the extent that

[6] The impact of Twitter on donations between $3000 and $5000, and donations above $5000, reported in Tables21 and 22of the Appendix

campaign expenditures capture other activities of the politician around the same time as opening a Twitter account, this result provides a reassuring check for our identification strategy.

6.2.2 News and Blogs Coverage

It is also possible that politicians join Twitter as part of their information campaigns, and opening Twitter accounts coincide with the spikes in coverage of these politicians by traditional media outlets. Media mentions of a politician might capture both additional information shocks voters receive and events a politician is involved in (which may not be reflected in campaign expenditures) which drive donations independently of Twitter. To address this concern, we collect data on the media mentions of a politician. We run a search for each politician's name in Google News and Google Blogs for a ± 10 week window around the time of opening of their twitter account[7]. Table 7 reports the results of this estimation. We use the total number of mentions in the news as the main dependent variable in our specification. Overall, the estimates in Table 7 suggest that being on Twitter interacted with Twitter penetration is not significantly associated with the number of news mentions (columns (1)-(4)) and this holds for both new (column (3)) and experienced politicians (column (4)). Moreover, we find that these results also hold when we look at the number of blog mentions as the dependent variable in Table 7 (columns (5)-(8)), as the coefficient for Twitter entry and penetration interaction remains insignificant and is actually negative in all the specifications.[8]

6.2.3 Twitter Entry, Twitter Penetration and Demographics

A further concern about our identification strategy is that Twitter penetration merely serves as a proxy for the income, education, or other socioeconomic characteristics of the state, and what we observe is a higher responsiveness to the shock (joining Twitter) in richer, more educated, or more liberal places. To ensure that it is not the case, we conduct another check. In particular, we test whether donations received can be explained by differential effects of entry on Twitter with different socioeconomic controls, such as the median household income in a state, the share of people who earn over $250,000 annually, the share of people with a college education, the share of people who voted for Bush in 2004 as well as the share of African Americans in the state. We report these results in Table 8. Our results suggest that the interaction of being on Twitter with each of these controls is insignificant both economically and statistically (columns (2)-(6)). [9]

[7]We search for the full name of the politician and record the number of hits we find on Google News and Google Blogs.

[8]Another relevant issue to address is a check on politicians' use of other social media platforms such as Facebook. To test the robustness of our results, we collected information on when each politician opened her Facebook account (if she did) and we find no robust relationship between having a Facebook account before and being on Twitter and Twitter penetration interaction (See Table 16 in the Appendix).

[9]We carry out similar checks to find that being on Twitter (interacted with socioeconomic controls) is not driving Twitter penetration or alternatively, that there is no significant higher probability of entry in states with

Overall, while we cannot test our identifying assumption directly, the placebo checks in this section suggest that unobserved heterogeneity, and other potentially simultaneous campaign activities in particular, are not driving our results.

6.3 Mechanisms

The main findings suggest that a politician's adoption of Twitter causes an increase in the aggregate donations she receives. There could be different channels through which Twitter affects the behavior of donors. The first one is an information channel. Opening a Twitter account allows the politicians to access a new, relatively inexpensive, channel of communication with its potential constituents. Moreover, information on the politicians' ability and policy stance are distributed at a low cost through social media. For donors who do not know about a candidate or are uninformed of her policies, this channel serves to create awareness. An alternate, second mechanism could be a persuasion channel. For potential donors who already know the candidate, communication via Twitter can create repeated exposure and persuade them to contribute more. This channel is akin to persuasive advertising in the Industrial Organization literature.

Our findings demonstrate that social media raises donations only for the new politicians and not for the experienced ones. This is in line with our theoretical framework where the marginal return to information provision through Twitter is likely to be low for the experienced candidates, since their quality, experience and policy positions are already better known. For a newcomer, there are no barriers to opening an account on Twitter and information dissemination through online word of mouth is possible at a relatively low cost. Our main result, that joining Twitter only helps inexperienced politicians, is thus consistent with the information mechanism.

In this section, we present a number of additional tests that allow us to check what mechanisms our data is consistent with. First, we check whether our estimates are stronger for new or repeat donors. We classify each donor as new if no donor with the same first and last name has contributed to a particular Congressional candidate before. Next, we check whether Twitter effects are stronger or weaker in places with high newspaper circulation. Finally, we also analyze Tweeting activities by politicians to document how different Tweeting activity and content of Tweets affects donations.

6.3.1 Probability of Receiving a Donation and New Donors

We conjecture that a politician's presence on social media have two possible ways of influencing donors. First, it is possible that a politician's presence simply changes the amount individuals contribute without altering the donor population. A second plausible argument in line with the

higher Twitter penetration. We analyze this in terms of levels and first differences of weekly Twitter penetration but find no economic or statistically significant relationship (See Table 17 and 18 in the Appendix).

postulated information channel is expanding the donor base, with new donors hearing about and contributing to the campaign for the first time. When the second explanation holds, being on Twitter will affect the probability of receiving donations as well. We provide evidence that indeed Twitter presence is associated with new donors rather than just a shift in the donation amounts of old donors.

From Table 4, one can see that if a politician joins Twitter in a high penetration state then it increases the probability of getting a donation by approximately 5% when looking at both new and experienced politicians together. This effect is statistically significant at the 5% level and is robust to inclusion of a week time trend (column (4)) as well other demographic controls (column (5)). When we split the sample into new and experienced politicians (columns (6) and (7)), we find that the effect of being on Twitter increases the probability of receiving a donation by 8% for new politicians while experienced politicians do not derive any significant benefit.

Next, we analyze the profile of donors. We split the donations received by politicians into those received from new and repeat donors to re-estimate our diff-in-diff specifications. Panel A of Table 9 shows the results for new donors which we find are in line with our information hypothesis. Using Twitter in a high penetration state leads to an increase in aggregate donations received from new donors (columns (1)-(2)) but splitting the sample into new and experienced politicians shows that new donors donate more to only new politicians (column (3)) and not to the experienced ones (column (4)). The same results hold when, instead, we look at receiving at least one donation per week as the dependent variable (columns (5)-(8)). Panel B of Table 9 shows the estimation for old donors. We do not find any effect of being on Twitter on donations received from old donors for either new or experienced politicians for aggregate donations and for receiving at least one donation per week. This, again, is consistent with the explanation that Twitter is expanding the donor base by providing increased awareness about politicians or their policies.

6.3.2 Social and Traditional Media as Substitute Channels of Communication

We analyze whether politicians who open a Twitter account communicate with the electorate via a new channel because their opportunities to do so through traditional channels such as newspapers are limited . To explore this possibility, we re-estimate our benchmark specification considering newspaper circulation of the region the politician is from, separately for low and high newspaper circulation regions.[10]

Panel A of Table 10 shows the estimates for states which have newspaper circulation per capita lower than the median while Panel B captures the effects for states with higher than median circulation. In Panel A, one can see that new politicians using Twitter in higher penetration though low newspaper circulation areas get a significantly higher amount of aggregate donations

[10]Low (high) circulation refers to circulation per capita below (above) the median circulation per capita across states.

(columns (1)-(4)) as well as a higher probability of getting at least one donation per week (columns (5)-(8)). Panel B shows that the effects hold for new politicians (columns (3) and (7)) in high newspaper circulation states but the effect is weaker statistically and quantitatively.The results are suggestive of a substitution pattern between social and traditional media.

Overall, this is in line with the information channel whereby Twitter provides an outlet for communication where other channels of communication such as traditional media are limited.

6.3.3 Tweeting Activity and Tweet Content

The results till now indicate that Twitter activity benefits new politicians by attracting new donors with the more experienced politicians not getting any bang for the buck from Twitter. To document how newer politicians might be attracting more donations, we analyze their Tweeting activity along with the content of their Tweets.

To analyze this, we focus on the coefficient on the triple interaction term between being on Twitter x Twitter penetration x different measures of Tweeting activity. We use measures of popularity of the politicians' Tweets such as the number of Retweets and the Favorite count of their Tweets. We find that this triple interaction term for Retweets is positive and significant for new politicians (column (3) of Table 11) and the effect is stronger in areas of higher Twitter penetration but the effect does not hold for the experienced politicians as seen in column (4). The results are qualitatively similar for when we use the number of Favorites as an alternative measure of popularity (columns (5)-(8)). The potential social contagion effect of Retweeting activity working only for new politicians is in line with our model where the increase in information has a higher payoff to the relatively lesser known candidates.[11]

Next, we move on to analyzing the content of the politicians' Tweets. It is possible that newer politicians use Twitter as a channel to inform their supporters of their positions and plans, or tell them to take part in the campaigning activities. In terms of the content, we find that in about 2-3% of the total Tweets made there is a hyperlink/URL which would provide information to their followers. We find that using these links leads to significantly higher donations to new politicians and the effect is larger in high penetration areas (column (3) in Table 12) while it has no impact for experienced politicians even in relatively higher Twitter penetration areas (column(4)).[12] Moreover using more 'inclusive' pronouns such as 'We' in their Tweets helps new politicians gain more donations while not helping the more experienced ones (columns (7) and (8) of Table 12).

[11] In terms of simple means we find that more experienced politicians send a larger number of Tweets and get a larger number of Retweets and Favorite counts as seen in Table 2. Moreover, we find that a higher number of Tweets on their own have no economically or statistically significant impact on the amount of donations received (see Table 19 (columns (1)-(4)) in the Appendix).

[12] We show that using words which relate directly to giving (e.g. 'donate', 'contribute', 'volunteer', 'help', etc.) have no impact on raising donations (See Table A7 (columns (5)-(8)) in the Appendix).

7 Discussion and Robustness Checks

7.1 Heterogeneous Effects Between Democrats and Republicans

Republican and Democratic voters have traditionally differed in demographic characteristics. Democratic voters are generally younger, ethnically more diverse, have higher education, are religiously unaffiliated, and have lower income. One or more of these characteristics may correlate with internet or social media useimplying that candidates registered with the Democratic Party may have higher returns from being on Twitter because the medium appeals to their constituents. We test for whether Twitter has an asymmetric effect on donations received across candidates from these two parties by splitting the sample and looking at our diff-in-diff estimates.

Panel A of Table 20 (in the Appendix) shows the estimates for the Democrats while Panel B demonstrates the effects for Republicans. In Panel A, one can see that new Democrat politicians using Twitter in higher penetration areas get a significantly (at the 1% level) higher amount in aggregate donations (columns (1)-(4)) and have higher probability of receiving at least one donation per week (columns (5)-(8)). As in the results for the whole sample, experienced Democratic politicians do not gain from this exercise. From Panel B, one can see that the effects hold for new Republican politicians (columns (3) and (7)) but it is substantially weaker statistically (significant at the 10% level). Overall, these results show that Twitter adoption has heterogeneous effects across the two party candidates and Democrats gain substantially more from it.

7.2 Excluding the Year 2009

One concern related to our baseline estimation is that the disproportionate number of accounts opened in 2009. While allowing for politician-month fixed effects and a week time trend (or week fixed effects) to account for any idiosyncrasies of a particular time period, we would not want our estimates to be driven by only one year's worth of data. Hence, as a robustness check, we exclude any accounts opening in 2009 and re-estimate our baseline specification.

Table 14 in the Appendix shows that the results remain in line with our baseline estimates with the whole sample both qualitatively and quantitatively. Being on Twitter in a high penetration state leads to higher aggregate donations (columns (1) to (4)) as well the probability of getting at least one donation per week (columns (5) to (8)) but these effects hold only for new politicians and not the more experienced ones. This is exactly the takeaway from our main estimates with the full sample.

7.3 Excluding Campaign Periods

The main concern associated with our identification is other events such as campaign activities happening at the same time with opening a Twitter account which might be driving donations. While our placebo checks provide confidence that this indeed not the case, we conduct another test to check the robustness of our results. Since elections take place in even numbered years (2010, 2012 and 2014 in our sample), it is likely that in the first half of each of the odd numbered years (2009, 2011, 2013) there would be limited campaign activity. Hence, we re-estimate our diff-in-diff specifications with only the first six months of 2009, 2011 and 2013.

In Table 15 in the Appendix, we find that even when we focus only on this disconnected 18 month period, the effect of using Twitter in a high penetration state persists for new politicians (columns (2) and (5)) while results remain insignificant for the experienced ones (columns (3) and (6)). Putting both types of politicians together (columns (1) and (4)) leads to insignificant results presumably because of a lack of power and limited variation since we only use a quarter of the entire data.

8 Conclusion

Electoral campaigns in the past decade have seen a significant change in the communication channels used by the candidates to reach out to the electorate.[13] A notable change during this period was the intensified use of social media platforms to reach out and inform voters, partially eliminating the dependency on the traditional media outlets such as newspapers and television. The essential question remains, does the use of social media accounts by politicians fundamentally alter any aspect of electoral politics? More broadly, can innovations in communication technologies change the way political markets operate? In this study, we document that a politician's entry on Twitter can help new politicians to attract new donations. In sum, our results imply that social media can help to democratize electoral politics by reducing the barriers for new politicians to communicate with the public.

Many avenues of future research lie at the intersection of adoption of new communication technologies and political outcomes. Future studies can expand the findings from our study to investigate the extent of substitution between the new and traditional media channels. For instance, we do not study how political advertising and use of social media may be complements or substitutes in delivering information about the candidates and their policies to voters. Further, a unique feature of social media is enabling two-way communication and transforming the one sided political communication into a two-sided one. One additional feature of social media may be the ability to listen to citizens' concerns and responses to policy proposals. Finally, in

[13] Andrews, Natalie and Rebecca Ballhaus, Twitter Courts U.S. Presidential Campaigns With New Donations Service, *Wall Street Journal*, 2015.

our study we focus on the effect of opening a new channel of communication on candidates' fund raising, but being on Twitter will also influence the politicians who are in the office. Some of these activities in office may be influenced by politicians' presence on channels like Twitter, since accounts which allow citizens to engage in communication may force the politicians to be more accountable. All of the listed are important questions, and future studies may consider addressing them.

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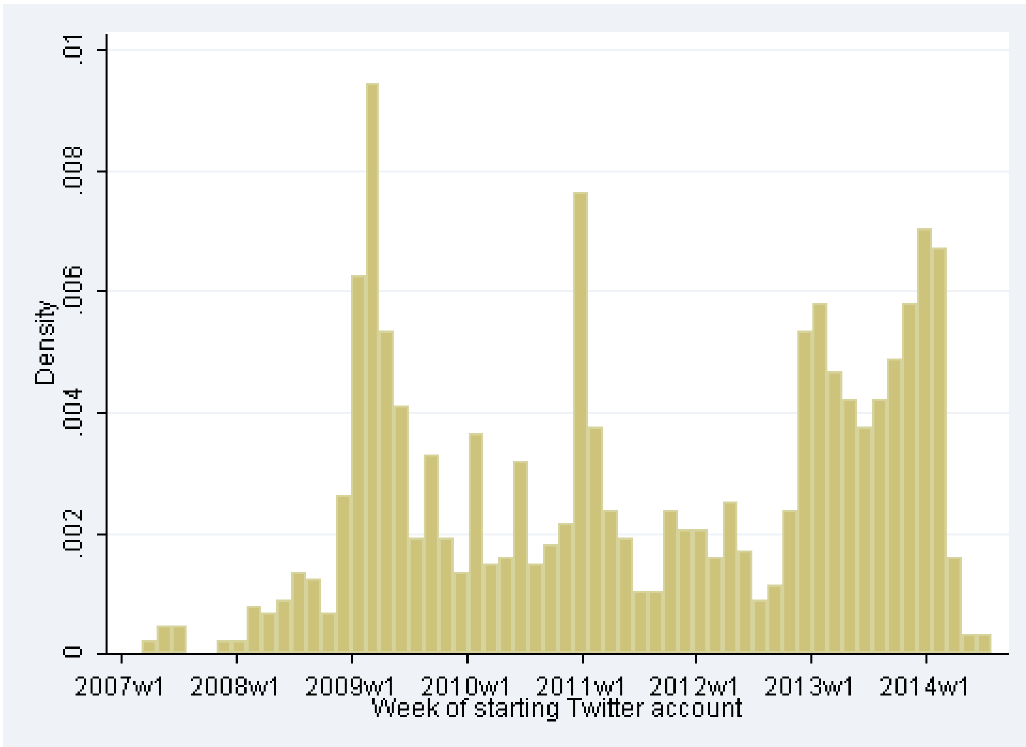

Figure 1: Date of Opening Accounts on Social Media

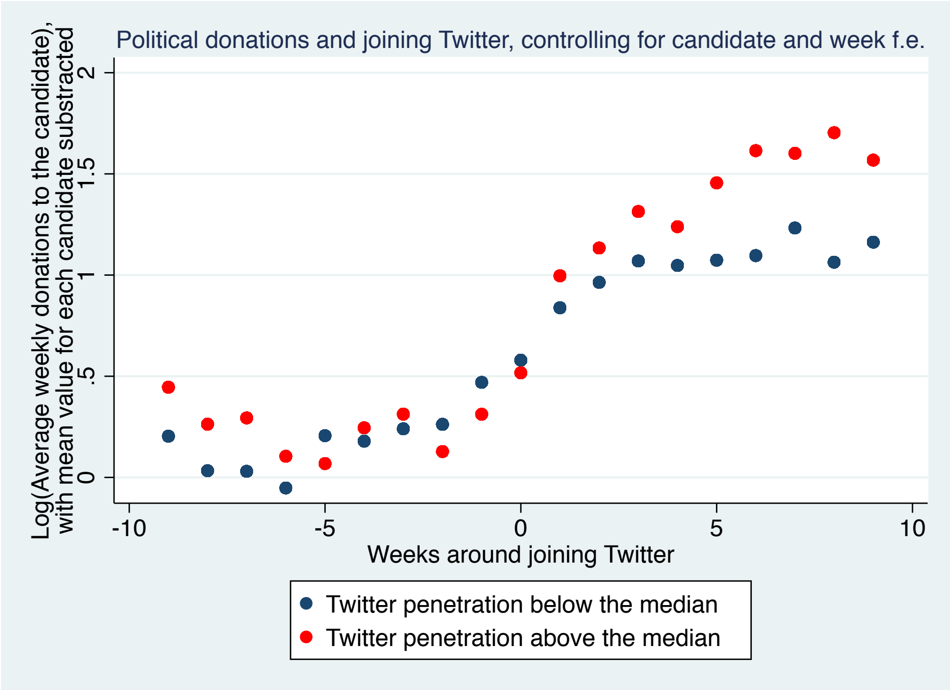

Figure 2: Donations and Twitter Penetration

Table 1: Summary Statistics: All Politicians

Variable	Observations	Mean	Std. Dev.	Min	Max
		All Politicians			
Log(Aggregate Donations)	1,834	1.99	2.03	0	9.48
Probability of Donations	1,834	0.25	0.24	0	0.99
Log (Campaign Expenditures)	1,834	2.53	2.74	0	11.24
Number of News Mentions	1,834	10.52	265.31	0	11,281.43
Number of Blog Mentions	1,834	6.99	158.13	0	6641.90
Facebook Account Before	1,834	0.02	0.14	0	1
Log(Number of Tweets)	1,834	0.11	0.28	0	1.98
Log(Number of Retweets)	1,834	0.12	0.40	0	4.91
Log(Number of Favorites)	1,834	0.04	0.21	0	3.66
Log(Proportion of URLs)	1,834	0.03	0.07	0	0.52
Log(Proportion of words)	1,834	0.003	0.008	0	0.09

Table 2: Summary Statistics: New and Old

Variable	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max
		New					Experienced			
Log(Aggregate Donations)	1,230	1.34	1.50	0	8.30	604	3.30	2.32	0	9.48
Probability of Donations	1,230	0.17	0.18	0	0.89	604	0.41	0.28	0	0.99
Log(Campaign Expenditure)	1,230	1.59	1.86	0	8.42	604	4.46	3.20	0	11.24
Number of News Mentions	1,230	4.93	37.77	0	946.85	604	30.41	526.51	0	11281.43
Number of Blog Mentions	1,230	3.91	36.43	0	780.52	604	18.77	310.72	0	6641.90
Facebook Account Before	1,230	0.01	0.09	0	0.98	604	0.05	0.20	0	1
Log(Number of Tweets)	1,230	0.09	0.26	0	1.89	604	0.13	0.32	0	1.98
Log(Number of Retweets)	1,230	0.09	0.30	0	2.50	604	0.18	0.54	0	4.91
Log(Number of Favorites)	1,230	0.02	0.11	0	1.16	604	0.09	0.32	0	3.66
Log(Proportion of URLs)	1,230	0.02	0.07	0	0.50	604	0.03	0.09	0	0.52
Log(Proportion of Words)	1,230	0.003	0.008	0	0.09	604	0.004	0.01	0	0.66
Log(proportion of ‘I’)	1,230	0.01	0.001	0	0.32	604	0.02	0.002	0	0.27
Log(proportion of ‘We’)	1,230	0.003	0.009	0	0.07	604	0.004	0.01	0	0.08

Table 3: Joining Twitter and Aggregate Donations: Baseline Estimates

VARIABLES	Log (aggregate donations)						
	(1) All Politicians	(2)	(3)	(4)	(5)	(6) New	(7) Experienced
on Twitter x Twitter penetration	-0.340***	0.359**	0.353**	0.349**	0.378**	0.692***	-0.217
	[0.117]	[0.148]	[0.147]	[0.147]	[0.144]	[0.169]	[0.256]
on Twitter	1.312***	0.435***	0.406***	0.161	0.700	-3.185	7.496*
	[0.116]	[0.104]	[0.103]	[0.100]	[2.404]	[3.268]	[4.450]
Log (campaign expenditure)			0.094***	0.091***	0.091***	0.121***	0.079***
			[0.004]	[0.004]	[0.004]	[0.007]	[0.004]
Politician-Month Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Time trend				Week	Week	Week	Week
Baseline controls x on Twitter					Yes	Yes	Yes
Observations	565,968	565,968	565,764	565,764	565,764	236,700	329,064
R-squared	0.019	0.820	0.821	0.823	0.823	0.885	0.787

Robust standard errors clustered at the level of the state in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the logarithm of aggregate donations in a week. Columns (1) - (5) includes all politicians while columns (6) includes only new ones and columns (7) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 4: Joining Twitter and the Probability of Donations

VARIABLES	Probability of Receiving at least one donation per week						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			All politicians			New	Experienced
on Twitter x Twitter penetration	-0.038***	0.048**	0.047**	0.047**	0.051**	0.084***	-0.014
	[0.014]	[0.020]	[0.019]	[0.019]	[0.019]	[0.024]	[0.034]
on Twitter	0.164***	0.047***	0.043***	0.021	0.023	-0.476	0.876
	[0.014]	[0.015]	[0.015]	[0.014]	[0.343]	[0.451]	[0.617]
Log (campaign expenditure)			0.011***	0.011***	0.011***	0.015***	0.009***
			[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Politician-Month Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Time trend				Week	Week	Week	Week
Baseline controls x on Twitter					Yes	Yes	Yes
Observations	565,968	565,968	565,764	565,764	565,764	236,700	329,064
R-squared	0.020	0.786	0.787	0.788	0.788	0.847	0.752

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the probability of receiving atleast one donation in a week. Columns (1)-(5) includes all politicians while column (6) includes only new ones while column (7) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 5: Joining Twitter and donations between $1000 and $3000

VARIABLES								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
on Twitter x Twitter penetration	0.205	0.236	0.573***	-0.380	0.030	0.033*	0.067***	-0.029
	[0.151]	[0.147]	[0.180]	[0.316]	[0.019]	[0.019]	[0.022]	[0.041]
on Twitter	0.262***	-1.125	-2.778	2.489	0.027**	-0.143	-0.317	0.223
	[0.097]	[2.346]	[2.368]	[4.194]	[0.013]	[0.269]	[0.275]	[0.515]
Log (campaign expenditure)	0.098***	0.098***	0.130***	0.086***	0.010***	0.010***	0.014***	0.009***
	[0.004]	[0.004]	[0.007]	[0.004]	[0.000]	[0.000]	[0.001]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	565,764	565,764	236,700	329,064	565,764	565,764	236,700	329,064
R-squared	0.759	0.759	0.826	0.722	0.727	0.727	0.791	0.690

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of aggregate donations in columns (1)-(4) and the probability of getting atleast one donation in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 6: Joining Twitter and Campaign Expenditures

VARIABLES	Log (campaign expenditures)					
	(1)	(2)	(3)	(4)	(5)	(6)
		All politicians			New	Experienced
on Twitter x Twitter penetration	-0.297**	0.036	0.035	0.063	0.233	-0.261
	[0.141]	[0.156]	[0.157]	[0.154]	[0.220]	[0.227]
on Twitter	1.481***	0.352***	0.269**	1.177	3.039	-1.230
	[0.145]	[0.105]	[0.106]	[2.550]	[3.321]	[2.810]
Politician-Month Fixed Effects		Yes	Yes	Yes	Yes	Yes
Time trend			Week	Week	Week	Week
Baseline controls x Twitter Penetration				Yes	Yes	Yes
Observations	565,764	565,764	565,764	565,764	236,700	329,064
R-squared	0.022	0.888	0.888	0.888	0.896	0.876

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of total campaign expenditures incurred in a week. Columns (1)-(4) includes all politicians while column (5) includes only new ones while column (6) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 7: News and Blogs Coverage

VARIABLES	#News				#Blogs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
on Twitter x Twitter penetration	-0.735	-0.627	0.217	-2.094	-0.518	-0.595	-0.0740	-1.528
	(1.051)	(0.966)	(0.254)	(2.984)	(1.033)	(0.918)	(0.151)	(2.776)
on Twitter	-0.164	8.073	0.0824	29.85	-0.179	1.638	-1.984	13.30
	(0.167)	(12.68)	(3.048)	(34.11)	(0.671)	(10.35)	(1.327)	(30.33)
Log (campaign expenditure)		-0.208	-0.586	0.132		-0.0177	-0.0626	0.0248
		(0.277)	(0.729)	(0.150)		(0.108)	(0.207)	(0.0843)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Baseline controls x on Twitter	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	47,375	47,356	28,947	18,409	47,375	47,356	28,947	18,409
R-squared	0.825	0.825	0.514	0.865	0.935	0.935	0.654	0.946

Robust standard errors clustered at the level of the state in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the number of news mentions in columns (1)-(4) and the number of blog mentions in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

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Table 8: Demographic Characteristics and Donations

VARIABLES	Log (aggregate donations per week)					
	(1)	(2)	(3)	(4)	(5)	(6)
on Twitter x penetration	0.349**					
	[0.147]					
on Twitter x median household income		-0.017				
		[0.015]				
on Twitter xshare of rich			-0.031			
			[0.083]			
on Twitter xshare of those with college education				-2.175		
				[1.839]		
on Twitter xvote share of Bush in 2004					0.164	
					[0.858]	
on Twitter xshare of African Americans						0.279
						[1.024]
onTwitter	0.161	1.112*	0.480**	2.161	0.323	0.374***
	[0.100]	[0.622]	[0.216]	[1.489]	[0.417]	[0.129]
Log (campaign expenditures)	0.091***	0.091***	0.091***	0.091***	0.091***	0.091***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week
Observations	565,764	565,764	565,764	565,764	565,764	565,764
R-squared	0.823	0.823	0.823	0.823	0.823	0.823

Notes: Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of total donations received in a week.

Table 9: Joining Twitter and donations from new and old donors

Panel A. Donations from new donors.

VARIABLES	Log (aggregate donations)				At least one donation per week			
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter	0.335***	0.343***	0.725***	-0.364*	0.045***	0.045***	0.090***	-0.039
	[0.119]	[0.119]	[0.159]	[0.208]	[0.016]	[0.016]	[0.022]	[0.029]
on Twitter x Twitter penetration	0.129	-0.929	-3.585	4.497	0.016	-0.172	-0.582	0.617
	[0.086]	[2.239]	[3.289]	[3.735]	[0.013]	[0.310]	[0.441]	[0.525]
Log (campaign expenditures)	0.069***	0.069***	0.094***	0.060***	0.008***	0.008***	0.011***	0.007***
	[0.004]	[0.004]	[0.007]	[0.004]	[0.001]	[0.001]	[0.001]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline Controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	565,764	565,764	236,700	329,064	565,764	565,764	236,700	329,064
R-squared	0.786	0.786	0.874	0.734	0.749	0.749	0.838	0.699

Panel B. Donations from new donors.

VARIABLES	Log (aggregate donations)				At least one donation per week			
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter	-0.085	-0.106	0.022	-0.319	-0.010	-0.013	0.002	-0.041
	[0.149]	[0.135]	[0.079]	[0.293]	[0.021]	[0.019]	[0.012]	[0.040]
on Twitter x Twitter penetration	0.108	2.679	-0.422	7.157*	0.018	0.380	0.047	0.838
	[0.100]	[2.046]	[1.547]	[3.778]	[0.014]	[0.279]	[0.242]	[0.516]
Log (campaign expenditures)	0.071***	0.071***	0.078***	0.068***	0.009***	0.009***	0.011***	0.009***
	[0.003]	[0.003]	[0.005]	[0.003]	[0.000]	[0.000]	[0.001]	[0.000]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	565,764	565,764	236,700	329,064	565,764	565,764	236,700	329,064
R-squared	0.764	0.764	0.810	0.737	0.731	0.731	0.766	0.705

Robust standard errors clustered at the level of the state in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the logarithm of total donation in a week from new donors in Panel A and from old donors in Panel B. In both panels, Columns (1)-(2) and (5)-(6) includes all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 10: Joining Twitter, Donations and Newspaper Circulation

VARIABLES	Log (aggregate donations)				At least one donation per week			
Panel A. Donations in Low Circulation States								
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.456**	0.489**	0.835***	-0.015	0.062**	0.063**	0.103***	0.003
	[0.224]	[0.229]	[0.244]	[0.433]	[0.030]	[0.031]	[0.034]	[0.060]
on Twitter	0.065	2.330	0.181	7.122	0.005	0.229	0.036	0.670
	[0.187]	[4.370]	[5.645]	[7.064]	[0.026]	[0.616]	[0.804]	[0.984]
Log (campaign expenditures)	0.089***	0.089***	0.120***	0.078***	0.010***	0.010***	0.014***	0.009***
	[0.006]	[0.006]	[0.012]	[0.007]	[0.001]	[0.001]	[0.002]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	229,556	229,556	95,831	133,725	229,556	229,556	95,831	133,725
R-squared	0.809	0.809	0.882	0.768	0.774	0.774	0.845	0.732
Panel B. Donations in High Circulation States								
VARIABLES	Log (aggregate donations)				At least one donation per week			
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.234	0.248	0.544**	-0.347	0.031	0.034	0.064*	-0.029
	[0.234]	[0.236]	[0.269]	[0.416]	[0.032]	[0.032]	[0.038]	[0.056]
on Twitter	0.248	0.271	-3.052	7.426	0.034	0.057	-0.451	1.067
	[0.168]	[3.194]	[3.692]	[5.996]	[0.023]	[0.448]	[0.529]	[0.810]
Log (campaign expenditures)	0.092***	0.092***	0.122***	0.080***	0.011***	0.011***	0.015***	0.010***
	[0.005]	[0.005]	[0.008]	[0.005]	[0.001]	[0.001]	[0.001]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	336,208	336,208	140,869	195,339	336,208	336,208	140,869	195,339
R-squared	0.832	0.832	0.887	0.799	0.797	0.797	0.848	0.766

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of total donation in a week from new donors in Panel A and from old donors in Panel B. In both panels, Columns (1)-(2) and (5)-(6) includes all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 11: Politicians' ReTweets and Favorites

VARIABLES	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
onTwitter x Twitter penetration x log(retweets)	0.436**	0.379*	1.510*	-0.129				
	(0.206)	(0.206)	(0.861)	(0.350)				
onTwitter x Twitter penetration x log(favorites)					0.0570	-0.0688	14.65***	-0.792
					(1.154)	(1.167)	(3.462)	(0.817)
onTwitter x log(retweets)	-0.432*	-0.369	-0.799*	0.138				
	(0.229)	(0.228)	(0.411)	(0.388)				
onTwitter x log(favorites)					0.241	0.367	-3.885***	0.789
					(1.211)	(1.224)	(1.288)	(0.939)
Twitter penetration x log(retweets)	-0.476**	-0.415**	-1.586*	0.135				
	(0.204)	(0.203)	(0.860)	(0.347)				
Twitter penetration x log(favorites)					-0.0899	0.0348	-14.96***	0.803
					(1.146)	(1.160)	(3.495)	(0.815)
log(retweets)	0.518**	0.444*	1.074***	-0.134				
	(0.226)	(0.225)	(0.399)	(0.381)				
log(favourites)					-0.195	-0.323	4.288***	-0.824
					(1.190)	(1.204)	(1.269)	(0.931)
onTwitter	0.434***	0.712	-3.337	7.477*	0.434***	0.679	-3.166	7.378
	(0.103)	(2.411)	(3.303)	(4.454)	(0.103)	(2.418)	(3.266)	(4.474)
onTwitter x Twitter penetration	0.357**	0.376**	0.697***	-0.219	0.359**	0.379**	0.693***	-0.213
	(0.148)	(0.144)	(0.169)	(0.257)	(0.148)	(0.144)	(0.169)	(0.257)
Log(campaign expenditure)		0.0905***	0.121***	0.0791***		0.0906***	0.121***	0.0792***
		(0.00408)	(0.00726)	(0.00434)		(0.00408)	(0.00734)	(0.00434)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend		Week	Week	Week		Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	565,968	565,764	236,700	329,064	565,968	565,764	236,700	329,064
R-squared	0.820	0.823	0.885	0.787	0.820	0.823	0.885	0.787

Robust standard errors clustered at the level of the state in parenthesis. {*}{*}{*} p$<$0.01, {*}{*} p$<$0.05, {*} p$<$0.1. The dependent variable is the logarithm of aggregate donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over \$250,000 a year, the median household income as well as the share of the population with a college degree.

Table 12: Tweet Content: #URLs and #We

VARIABLES	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
onTwitter x Twitter penetration x log(links)	0.865*	0.709	9.443**	-0.333				
	(0.500)	(0.495)	(4.167)	(0.389)				
onTwitter x Twitter penetration x log(#we)					1.500	1.595	11.31*	-0.313
					(1.488)	(1.557)	(5.639)	(2.592)
Twitter penetration x log(links)	-1.020**	-0.867*	-9.758**	0.345				
	(0.502)	(0.497)	(4.308)	(0.378)				
Twitter penetration x log(#we)					-1.554	-1.643	-12.97**	0.516
					(1.518)	(1.591)	(6.030)	(2.642)
onTwitter x log(links)	-0.994*	-0.852	-4.337**	0.612				
	(0.568)	(0.595)	(1.682)	(0.650)				
onTwitter x log(#we)					-1.554	-1.643	-12.97**	0.516
					(1.518)	(1.591)	(6.030)	(2.642)
log(links)	1.331**	1.178**	5.071***	-0.563				
	(0.558)	(0.584)	(1.760)	(0.627)				
log(#we)					0.627	0.621	4.499*	-0.750
					(1.061)	(1.110)	(2.352)	(2.669)
onTwitter x Twitter penetration	0.365**	0.384**	0.714***	-0.218	0.353**	0.378**	0.694***	-0.218
	(0.148)	(0.144)	(0.169)	(0.256)	(0.147)	(0.144)	(0.169)	(0.256)
onTwitter	0.423***	0.676	-3.285	7.476*	0.405***	0.698	-3.180	7.496*
	(0.104)	(2.399)	(3.283)	(4.456)	(0.103)	(2.404)	(3.275)	(4.450)
log(campaign expenditure)		0.0906***	0.121***	0.0792***		0.0941***	0.0906***	0.121***
		(0.00408)	(0.00729)	(0.00434)		(0.00407)	(0.00408)	(0.00730)
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	565,968	565,764	236,700	329,064	565,968	565,764	236,700	329,064
R-squared	0.820	0.823	0.885	0.787	0.820	0.823	0.885	0.787

Robust standard errors clustered at the level of the state in parenthesis. {*}{*}{*} p$<$0.01, {*}{*} p$<$0.05, {*} p$<$0.1. The dependent variable is the logarithm of aggregate donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over \$250,000 a year, the median household income as well as the share of the population with a college degree.

Table 13: Joining Twitter, Aggregate Donations and Different Window Sizes

VARIABLES	Log (aggregate donations)				
	(1)	(2)	(3)	(4)	(5)
Window size	±5 weeks	±10 weeks	±25 weeks	±50 weeks	±300 weeks
on Twitter x penetration	0.371**	0.373**	0.376**	0.377**	0.378**
	[0.152]	[0.148]	[0.145]	[0.144]	[0.144]
on Twitter	0.347	0.496	0.598	0.635	0.702
	[2.586]	[2.501]	[2.436]	[2.416]	[2.404]
Log (campaign expenditure)	0.144***	0.137***	0.106***	0.097***	0.091***
	[0.016]	[0.010]	[0.007]	[0.006]	[0.005]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week
Baseline controls x on Twitter	Yes	Yes	Yes	Yes	Yes
Observations	14,562	30,341	75,203	144,110	507,537
R-squared	0.761	0.767	0.796	0.805	0.818

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of total donations received in a week. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 14: Joining Twitter and Donations without 2009

VARIABLES	Log (aggregate donations per week)				At least one donation per week			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
on Twitter x Twitter penetration	0.589 ***	0.706***	0.932***	0.163	0.083***	0.098***	0.123***	0.037
	[0.183]	[0.187]	[0.230]	[0.348]	[0.024]	[0.026]	[0.033]	[0.049]
on Twitter	-.183	-2.649	-8.584*	7.128	-0.030	-0.531	-1.350**	0.784
	[0.186]	[3.505]	[4.547]	[6.443]	[0.027]	[0.513]	[0.608]	[0.882]
Log (campaign expenditure)	.089***	0.089***	0.116***	0.079***	0.010***	0.011***	0.014***	0.009***
	[0.004]	[0.005]	[0.009]	[0.005]	[0.0006]	[0.001]	[0.001]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	471,467	471,467	172,989	298,478	471,467	471,467	172,989	298,478
R-squared	0.826	0.827	0.886	0.797	0.79	0.79	0.847	0.762

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of aggregate weekly donations in columns (1)-(4) and the probability of receiving atleast one donation in columns (5)-(8). This considers a sub-sample without 2009. Columns (1)-(2) and (5)-(6) includes all politicians while columns (3) and (7) includes only new ones and columns (8) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 15: Joining Twitter Outside Campaign Periods

VARIABLES	Log (aggregate donations)					
	(1)	(2)	(3)	(4)	(5)	(6)
	All politicians	New	Experienced	All politicians	New	Experienced
on Twitter	0.505	1.124***	-0.185	0.049	0.126**	-0.033
	[0.318]	[0.405]	[0.454]	[0.046]	[0.057]	[0.065]
on Twitter x penetration	2.353	2.048	3.030	0.155	0.255	0.128
	[2.780]	[2.953]	[5.406]	[0.422]	[0.376]	[0.781]
Log (campaign expend)	0.095***	0.181***	0.081***	0.011***	0.021***	0.009***
	[0.007]	[0.019]	[0.006]	[0.001]	[0.003]	[0.001]
Politician-Month FE		Yes	Yes	Yes	Yes	Yes
Time trend				Week	Week	Week
Baseline controls					Yes	Yes
Observations	141,424	61,981	79,443	141,424	61,981	79,443
R-squared	0.794	0.881	0.757	0.761	0.841	0.721

Notes: Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of aggregate weekly donations. This considers politicians joining Twitter outside of campaign periods. Columns (1) and (4) includes all politicians while columns (2) and (4) includes only new ones and columns (3) and (6) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 16: Joing Twitter and Facebook Accounts

VARIABLES	Joined Facebook Before						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			All Politicians			New	Experienced
on Twitter x penetration	0.00708	-0.00160	-0.00160	-0.00161	-0.00220*	-0.000424	-0.00532
	(0.00498)	(0.00105)	(0.00105)	(0.00105)	(0.00130)	(0.000503)	(0.00350)
on Twitter	0.0298***	0.00246*	0.00245	0.00213	0.00960	0.00103	0.0244
	(0.00770)	(0.00146)	(0.00146)	(0.00146)	(0.0121)	(0.00505)	(0.0325)
Log (campaign expend)			2.62e-05	2.16e-05	2.17e-05	5.98e-05	7.59e-06
			(2.21e-05)	(2.18e-05)	(2.18e-05)	(5.95e-05)	(1.98e-05)
Politician-Month Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Time trend				Week	Week	Week	Week
Baseline controls x on Twitter					Yes	Yes	Yes
Observations	565,968	565,968	565,764	565,764	565,764	236,700	329,064
R-squared	0.012	0.996	0.996	0.996	0.996	0.993	0.997

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is whether the politician joined Facebook before joining Twitter. Columns (1)-(5) includes all politicians while column (6) includes only new ones and column (7) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 17: Twitter Entry, Demographics and Twitter Penetration: Levels

VARIABLES	Twitter Penertation: Levels					
	(1)	(2)	(3)	(4)	(5)	(6)
onTwitter	-0.00003	-0.000145	-2.11e-05	-0.000184	-2.59e-05	1.43e-05
	[0.00003]	[0.0002]	[7.66e-05]	[0.0005]	[0.0001]	[4.17e-05]
on Twitter x median household income		4.16e-06				
		[5.28e-06]				
on Twitter xshare of rich			2.27e-05			
			[3.15e-05]			
on Twitter xshare of those with college education				0.0002		
				[0.0006]		
on Twitter xvote share of Bush in 2004					0.0001	
					[0.0002]	
on Twitter xshare of African Americans						[0.0001]
						[0.0002]
Log (campaign expenditures)	1.80e-06	1.80e-06	1.80e-06	1.80e-06	1.80e-06	1.80e-06
	[1.50e-06]	[1.50e-06]	[1.50e-06]	[1.50e-06]	[1.50e-06]	[1.50e-06]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week
Observations	565,764	565,764	565,764	565,764	565,764	565,764
R-squared	0.929	0.929	0.929	0.929	0.929	0.929

Notes: Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of weekly Twitter penetration.

Table 18: Twitter Entry, Demographics and Twitter Penetration: First Differences

VARIABLES	Twitter Penertation: First Difference					
	(1)	(2)	(3)	(4)	(5)	(6)
onTwitter	-0.00001	-9.08e-05	2.36e-05	-0.0007	-0.0002	-4.84e-05
	[0.009]	[0.0002]	[0.0001]	[0.0007]	[0.00003]	[6.68e-05]
on Twitter x median household income		1.77e-06				
		[6.70e-06]				
on Twitter xshare of rich			-1.63e-05			
			[4.30e-05]			
on Twitter xshare of those with college education				0.0008		
				[0.0009]		
on Twitter xvote share of Bush in 2004					0.0003	
					[0.0004]	
on Twitter xshare of African Americans						0.0002
						[0.0004]
Log (campaign expenditures)	1.61e-06	1.61e-06	1.61e-06	1.61e-06	1.61e-06	1.62e-06
	[1.72e-06]	[1.74e-06]	[1.74e-06]	[1.74e-06]	[1.74e-06]	[1.74e-06]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week
Observations	563,951	563,951	563,951	563,951	563,951	563,951
R-squared	0.104	0.105	0.105	0.105	0.105	0.105

Notes: Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the weekly Twitter penetration in first differences.

Table 19: Politician Tweets: Number of Tweets and Tweet Content

VARIABLES	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
onTwitter x Twitter penetration x log(tweets)	0.420*	0.357	0.841	0.0441				
	(0.213)	(0.218)	(1.197)	(0.165)				
onTwitter x Twitter penetration x log(words)					0.345	0.427	-8.146	0.995
					(0.982)	(0.960)	(6.470)	(1.154)
onTwitter x log(tweets)	-0.521**	-0.454**	-0.612	-0.0836				
	(0.224)	(0.224)	(0.393)	(0.296)				
onTwitter x log(words)					-0.732	-0.777	1.877	-0.882
					(0.953)	(0.938)	(2.387)	(1.145)
Twitter penetration x log(tweets)	-0.526**	-0.462**	-0.837	-0.0535				
	(0.220)	(0.225)	(1.214)	(0.163)				
Twitter penetration x log(words)					-0.529	-0.583	7.641	-1.091
					(0.954)	(0.934)	(6.448)	(1.128)
log(tweets)	0.738***	0.665***	0.928**	0.130				
	(0.225)	(0.225)	(0.409)	(0.287)				
log(words)					1.302	1.269	-1.191	1.278
					(0.905)	(0.890)	(2.393)	(1.081)
onTwitter	0.388***	0.547	-3.699	7.505*	0.431***	0.696	-3.214	7.507*
	(0.105)	(2.401)	(3.248)	(4.458)	(0.104)	(2.406)	(3.276)	(4.446)
onTwitter x Twitter penetration	0.386**	0.406***	0.755***	-0.217	0.361**	0.379**	0.695***	-0.218
	(0.149)	(0.144)	(0.173)	(0.257)	(0.148)	(0.144)	(0.169)	(0.256)
Log(campaign expenditure)		0.0905***	0.120***	0.0791***		0.0906***	0.121***	0.0792***
		(0.00409)	(0.00731)	(0.00434)		(0.00408)	(0.00732)	(0.00434)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend		Week	Week	Week		Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	565,968	565,764	236,700	329,064	565,968	565,764	236,700	329,064
R-squared	0.820	0.823	0.885	0.787	0.820	0.823	0.885	0.787

Robust standard errors clustered at the level of the state in parenthesis. {*}{*}{*} p$<$0.01, {*}{*} p$<$0.05, {*} p$<$0.1. The dependent variable is the logarithm of aggregate donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over \$250,000 a year, the median household income as well as the share of the population with a college degree.

Table 20: Joining Twitter and Donations: Democrats vs. Republicans

Panel A. Donations to Democrats.

VARIABLES	Log (aggregate donations)				At least one donation per week			
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.648**	0.605**	1.024***	-0.154	0.085***	0.075**	0.119***	-0.005
	[0.251]	[0.255]	[0.282]	[0.458]	[0.029]	[0.030]	[0.039]	[0.052]
on Twitter	0.071	-1.995	-6.551	5.312	0.003	-0.412	-0.988	0.486
	[0.185]	[4.052]	[4.924]	[6.135]	[0.024]	[0.554]	[0.676]	[0.761]
Log (campaign expenditures)	0.087***	0.087***	0.117***	0.077***	0.010***	0.010***	0.014***	0.009***
	[0.006]	[0.006]	[0.011]	[0.007]	[0.001]	[0.001]	[0.002]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline Controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	234,823	234,823	92,218	142,605	234,823	234,823	92,218	142,605
R-squared	0.827	0.827	0.904	0.787	0.790	0.790	0.869	0.748

Panel B. Donations to Republicans.

VARIABLES	Log (aggregate donations)				At least one donation per week			
	All		New	Experienced	All		New	Experienced
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.133	0.188	0.414*	-0.248	0.021	0.029	0.054*	-0.019
	[0.214]	[0.215]	[0.221]	[0.410]	[0.030]	[0.030]	[0.032]	[0.056]
on Twitter	0.212	2.755	-1.257	10.294*	0.031	0.372	-0.168	1.398
	[0.154]	[3.643]	[4.171]	[6.083]	[0.022]	[0.525]	[0.611]	[0.862]
Log (campaign expenditures)	0.093***	0.093***	0.123***	0.081***	0.011***	0.011***	0.015***	0.010***
	[0.005]	[0.005]	[0.008]	[0.006]	[0.001]	[0.001]	[0.001]	[0.001]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	330,941	330,941	144,482	186,459	330,941	330,941	144,482	186,459
R-squared	0.818	0.818	0.871	0.785	0.785	0.785	0.832	0.754

Robust standard errors clustered at the level of the state in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the logarithm of total donation in a week for Democratic candidates in Panel A and for Republicans in Panel B. In both panels, Columns (1)-(2) and (5)-(6) includes all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 21: Joining Twitter and Aggregate Donations ($3000-$5000)

VARIABLES	(1) All	(2)	(3) New	(4) Experienced	(5) All	(6)	(7) New	(8) Experienced
on Twitter x Twitter penetration	0.018	0.037	0.033	0.039	0.003	0.005	0.005	0.005
	[0.048]	[0.049]	[0.061]	[0.095]	[0.006]	[0.006]	[0.007]	[0.011]
on Twitter	-0.001	-0.856	-1.305	-0.143	-0.001	-0.085	-0.132	-0.012
	[0.045]	[0.703]	[0.957]	[0.870]	[0.005]	[0.077]	[0.102]	[0.102]
Log (campaign expenditure)	0.012***	0.012***	0.019***	0.010***	0.001***	0.001***	0.002***	0.001***
	[0.001]	[0.001]	[0.003]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	565,764	565,764	236,700	329,064	565,764	565,764	236,700	329,064
R-squared	0.539	0.539	0.572	0.523	0.518	0.518	0.547	0.502

Robust standard errors clustered at the level of the state in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the logarithm of aggregate donations in columns (1)-(4) and the probability of getting atleast one donation in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Table 22: Joining Twitter and Aggregate Donations (Above $5000)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All		New	Experienced	All		New	Experienced
on Twitter x Twitter penetration	0.011	0.024	0.008	0.046	0.002	0.003	0.001	0.006
	[0.045]	[0.047]	[0.054]	[0.095]	[0.005]	[0.005]	[0.006]	[0.011]
on Twitter	-0.009	-1.048	-1.091	-1.055	-0.001	-0.102	-0.111	-0.097
	[0.043]	[0.877]	[1.055]	[1.144]	[0.005]	[0.094]	[0.115]	[0.117]
Log (campaign expenditure)	0.016***	0.016***	0.031***	0.011***	0.002***	0.002***	0.003***	0.001***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Baseline controls x on Twitter	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	565,764	565,764	236,700	329,064	565,764	565,764	236,700	329,064
R-squared	0.591	0.591	0.604	0.584	0.566	0.566	0.583	0.558

Robust standard errors clustered at the level of the state in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable is the logarithm of aggregate donations in columns (1)-(4) and the probability of getting atleast one donation in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) includes only new ones and columns (4) and (8) has the experienced politicians. Baseline controls, at the level of the state, are interacted with the politician being on Twitter, include the share of the population who voted for Bush in 2004, the percentage of African-American population, the share of population which earns over $250,000 a year, the median household income as well as the share of the population with a college degree.

Appendix: Data

Notes on Data Collection from Twitter

We provide guidelines for Twitter data collection here. Twitter allows researchers and developers to pull data from API in two different forms.

1. **REST API.** The API allows researchers to look up any user or tweet from the past conditional on a unique identifier (i.e. a user's Twitter handle, a tweet's ID, etc). However, Twitter places pretty tight constraints on the amount of data one can get in a given window of time. Due to the limitations in data gathering, we use the REST API to collect information about the politicians and their tweets.

2. **Streaming API.** This API is the most commonly used tool for gathering Twitter data in academic research. The Streaming API allows researchers to tap into 1% of all incoming tweets in a random fashion and without the data extraction limits of the REST API. Via the Streaming API, we are unable to obtain every tweet posted on Twitter, but we obtain a consistent random sample of them. We use this API when we need massive amounts of data: the followers' profile information and their tweeting activity data.

Verification of Politician Twitter Accounts. After data collection, a research assistant who is blind to the research question manually verified the politician accounts. The verification of the politician accounts could also partially be handled via the Twitter API field verified which shows whether or not an account is verified. However, some congressman hold unverified accounts, although from the posted information on the profiles, it is plausible to assume the accounts are authentic.

Searching for a Candidate's Account. The search for a candidate account on Twitter is initiated by searching for each candidate's name via the Twitter API, and deduced which handle was his or hers algorithmically and subsequently checked manually by an RA.