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Social Media and Political Donations: New Technology and Incumbency Advantage in the United States*

Maria Petrova[†], Ananya Sen [‡], Pinar Yildirim [§]

Abstract

Can new technologies increase political competition? We study the impact of adopting Twitter on campaign contributions received by politicians. For identification, we compare donations just before and just after politicians open Twitter accounts in regions with high and low levels of Twitter penetration, controlling for politician-month fixed effects. We estimate that opening a Twitter account amounts to an increase of at least 2-3% in donations per campaign. This effect is stronger for new politicians, who were never elected before, for donations coming from new donors, for politicians who tweet more informatively, and for politicians from regions with lower newspaper circulation.

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1 Introduction

In a democratic society, electoral competition and low barriers to enter politics promote good policies and reduce corruption (e.g., Myerson, 1993; Persson et al., 2003; Besley et al., 2010; Ferraz and Finan, 2011; Galasso and Nannicini, 2011). Low political competition and incumbency advantage emerge when challengers do not have enough opportunities to inform voters about their candidacy and policy positions (Ansolabehere and Snyder, 2000; Prat, 2002; Strömberg, 2004; Prior, 2006). The persistent advantage enjoyed by experienced politicians over challengers is well documented. Incumbents are reported to achieve re-election rates around 90% (Levitt and Wolfram, 1997). They also receive higher levels of media coverage and endorsements, creating additional barriers to entry for new politicians. New communication technologies such as Twitter can mitigate the incumbency advantage by allowing new politicians to access an alternate, relatively cost-effective technology to communicate with their constituency about their candidacy, gain support and raise funds, but it is not clear if it is true empirically.

In this paper, we study the consequences of politicians' adoption of a new communication technology by focusing specifically on opening a Twitter account and its effect on the campaign contributions received while they are running for the U.S. Congress. We evaluate if adopting Twitter helps politicians to inform voters and increases the financial support received from them. To identify the effect, we test if the contributions politicians receive from individual donors change before and after joining Twitter, comparing regions with low and high Twitter penetration. We use data on 1814 politicians who opened a personal Twitter account between 2009 and 2014, campaign contributions they receive, and the usage of Twitter compared to other websites in the politician's region (i.e., Twitter penetration).

Identifying the causal impact of Twitter on political donations is not trivial, mainly because of correlated unobservables which could influence both a politician's decision to join Twitter and the amount of political donations she raises. We rely on the precise timing of opening an account in our estimation and control for the politician-month fixed effects to account for politician-specific unobserved time-varying factors, 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 char-

acteristics, would be the same in the absence of Twitter entry in states where Twitter has low and high penetration, i.e. it is a parallel trends assumption. However, we do not need to assume that politicians' decision to join Twitter is random or exogenous to their fund-raising activities.

The findings from our analysis suggest that adopting Twitter helps politicians to receive more contributions. Weekly aggregate contributions increase after a politician starts blogging on Twitter. However, this gain is positive only for new politicians who have never been elected to the Congress before, and not for the experienced candidates. The aggregate political contributions to an average new politician increases by at least $5,773, corresponding to 2-3% of all donations under $3000 received during a campaign. Associated persuasion rate due to opening a Twitter channel is approximately 1%. This rate is lower than average media persuasion rates reported in the literature (DellaVigna and Gentzkow, 2010), but is comparable to the persuasion rates for direct mailing (Gerber and Green, 2000) and political advertising (Spenkuch and Toniatti, 2016).

To explain the mechanism through which donations are raised, we borrow from the industrial organization literature on advertising (Nelson 1974). Adopting a new communication technology, similar to advertising, helps politicians to gain support through information and/or persuasion channel. The information mechanism suggests that voters who were not previously familiar with a candidate are informed about the candidate and their policy plans, and persuasion mechanism suggests that voters who are already informed about the candidates and their policy stances would be further persuaded to provide support. We provide evidence that information mechanism seems to explain the increase in donations. First, we find that entry to Twitter increases political donations from those donors who did not support particular politicians before, not from repeat donors. Second, an analysis of the tweet content suggests that the donations to candidates who tweet more informatively is higher. Third, we find that the effect is stronger for candidates running for shorter-term House of Representatives seats compared to the longer term Senate seats, likely because Senate elections receive more attention from the media and the candidates have a better chance to familiarize themselves with the electorate. Candidates for the House, on the other hand, have more to gain from raising awareness about their candidacy. Finally, we find that the gains from Twitter are higher

for the politicians running in low newspaper circulation states. Overall, these findings suggest that political contributions respond to politicians' adoption of Twitter, and information mechanism seems to explain why our results hold.

We use a series of placebo tests to ensure that our identifying assumption is plausible. First, we show that there is no discontinuous increase in a politician's campaign spending around the time of her Twitter entry across high and low Twitter penetration areas, even though political contributions are strongly correlated with campaign spending in a given week. Second, to control for possible exogenous events, which may coincide with Twitter entry and discontinuity in the funds raised, we show that media and blog coverage of the politicians do not change significantly around the time of Twitter entry, and there are no differences between the high and low Twitter penetration areas. Third, we find that there is no increase in advertising spending on TV around the time of Twitter entry. Finally, we ensure that opening an account for Twitter is not a proxy for other characteristics such as income, education, political preferences, and racial composition which may influence donations. We test if these characteristics predict donations and find that it is unlikely that Twitter penetration is just a proxy for one of those variables. Overall, the results in all our placebo specifications are consistent with our identifying assumption, i.e., parallel trend assumption.

A broader implication of our study is that the adoption of Twitter reduces the gap in fund-raising opportunities between new and experienced politicians, which, in turn, reduces barriers to entry to national politics and increases political competition. This implication is bolstered by the fact that we find qualitatively similar results when we analyze the impact of Facebook adoption on political donations. Thus, new technologies indeed can change the incentives of potential entrants and help to make American politics more competitive.

Our study contributes to several streams of the literature. First, our paper highlights how the advent of a new communication technology, social media in general and Twitter in particular, can intensify political competition by improving opportunities for new candidates to raise funds and inform voters in a cost-effective fashion. We thus complement the literature which documents the positive impact of political competition and lowering barriers to entering politics (Myerson, 1993; Persson et al., 2003; Besley et al., 2010; Ferraz and Finan, 2011; Galasso and Nannicini, 2011). 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 and Snyder (2000), as well as Prat (2002) and Prior (2006), study different sources of incumbency advantage, including lack of information of voters about the new candidates and lack of funding opportunities among the main factors.

Next, we contribute to the literature that studies the role of campaign contributions in political processes. Grossman and Helpman (1996, 2001) 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 (Prat, 2002; Coate, 2004; Ashworth, 2006; Drazen et al., 2007; Cotton, 2009, 2012; Chamon and Kaplan, 2013). In all these models, campaign contribution limits have different implications depending on whether advertising spending reveals some information about the types of politicians (Prat, 2002; Coate, 2004; Cotton, 2012) or enhances 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 social media can actually raise donations for inexperienced candidates.

Next, our paper is also related to the 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; Chiang and Knight, 2011; Gentzkow et al., 2014), violence and ethnic tensions (Adena et al., 2014; DellaVigna et al., 2014; Yanagizawa-Drott, 2014), social outcomes (Jensen and Oster, 2009; La Ferrara et al., 2012), and policy decisions (Strömberg, 2004; Eisensee and Strömberg, 2007; Snyder Jr and Strömberg, 2010). We complement this stream by highlighting a mechanism through which media could influence political fund raising opportunities. A number of earlier studies point to the challenges of measuring the benefits from social media (Lovett and Staelin, 2012; Bollinger et al., 2013; Culotta and Cutler, 2016; Ma et al., 2015) as well as the relationship between political positioning of media and their revenues (Gal-Or et al., 2012; Yildirim et al., 2013). Our findings suggest concretely that these platforms can generate positive returns.

Finally, we also contribute to the emerging literature on the impact of social media on various socioeconomic outcomes. Gong et al. (2015) and Seiler et al. (2016) study the impact of advertising of TV content in Chinese micro blogs on subsequent TV series viewership. Enikolopov, Petrova, and Sonin (2016) study the impact of social media on corporate accountability. Acemoglu et al. (2014) and Enikolopov et al. (2016) analyze the effects 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 (2013) look at the relationship between a Chinese microblog penetration on drug quality. In contrast with these studies, we focus our investigation on the strategic benefit of entry into an online social network for the politicians, quantifying their financial gain, and investigating mechanisms behind it in detail.

2 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 has been crucial for electoral success. Candidates further engage 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[1]. The content of this communication is more personal, compared with the regular campaign messages, and includes information about politicians' lives and activities outside of politics. While politicians who are well known and hold high level positions typically reach out to several million followers on Twitter, lesser known politicians communicate with several hundred to several thousand individuals. Barack Obama, in 2016, had over twenty-three million followers while Orin Hatch and Jared Polis had over thirty thousand accounts following them. In our data, the total number of Congressional candidates who had been using Twitter increases from 741 in 2009 to 1,024 in 2010, to 1,488 in 2012, and to 1,814 in 2014.

[1] http://www.adweek.com/socialtimes/world-leaders-twitter/495103, accessed in September 2016.

After the 2008 presidential 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 Ellison, 2010; Boyd and Marwick, 2011). Among these sites, Twitter is unique due to its confinement to 140-characters and the lack of restrictions on viewing messages from those with whom one is not directly connected to. Connections on Twitter are created based on the content of messages rather than real-life relationships, resulting in ties that span physical and social disparities (Virk et al., 2011). As of today, Twitter and other online SNSs are seen as complements to traditional outreach mediums (Towner and Dulio, 2012)Campante et al. (2013).

Scholars and pundits question whether the overall use of SNSs by politicians actually matters for political outcomes (Kushin and Yamamoto, 2010; Baumgartner and Morris, 2010; Zhang et al., 2010). The primary benefits of the SNS as a campaign tool are said to include low costs, recruitment of volunteers and contributions, and holding a space for lesser known candidates (Gueorguieva, 2008). 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. The direct communication with the constituency allows a candidate to bypass traditional media outlets (Lassen and Brown, 2010). A number of studies provide correlational evidence on how social media influences campaigns. Metaxas and Eni (2012) comment on the relationship between social media use and electoral outcomes, while Hong and Nadler (2011) demonstrate how the use of Twitter correlates with the shifts in polls during election periods. There are also reported challenges of managing a Twitter account, such as the need for constant monitoring and responding to audience interests (Boyd and Marwick, 2011), absence of authoritative hierarchies (Metzgar and Maruggi, 2009), and possible loss of control over a message (Gueorguieva, 2008; Johnson and Perlmutter, 2010). Although the number of Twitter users continues to increase, only a fraction of them report using the site to gather political information (Smith and Rainie, 2008; Smith, 2011). For politicians, policy makers, and consumers of social media, documenting the causal impact of Twitter with mechanisms at play is essential.

Media and Incumbency Advantage

Incumbency advantage is among the best-documented electoral patterns in the United States (Ansolabehere et al., 2006). Incumbents reportedly enjoyed increasing levels of electoral wins, starting with a 1-2% point advantage in the 1940s and ending in 8-10% advantage in the 2000s. Explanations for why known or incumbent politicians enjoy an advantage include the incumbents actually being higher quality candidates (Jacobson and Kernell, 1982), the access to the resources of the office they held (including the staff and committee positions to raise campaign funds)(Cox and Katz, 1996), and the extensive media attention they receive, compared with inexperienced politicians. Traditional media can influence voter decisions through its coverage and candidate endorsements. Voters also favor candidates whom they can recognize (Jacobsen, 1987). Survey-based findings suggest that incumbents enjoy higher media coverage and more frequent endorsements (Goldenberg and Traugott, 1980; Clarke and Evans, 1983; Ansolabehere et al., 2006), as compared with their opponents. Ansolabehere et al. (2006) find that endorsements influence the outcome of an election by about 1-5% points. These findings suggest that the experience of a candidate in politics - both due to her public recognition and due to holding a public office - can put new politicians at a disadvantage (Cox and Katz, 1996). Lower incentives for running for an office by entrants translate into less competitive races, which is correlated with lower responsibility and accountability towards constituents by politicians (Carson et al., 2007). These concerns together suggest that new technologies, which can reduce the incumbency advantage, can help elections to be more competitive. Complementing these earlier studies, our study finds that new rather than the experienced politicians have an advantage in opening an account on social media promising to mitigate the incumbency advantage.

3 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 data.

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, θ_i . 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 competence, honesty, or experience of a politician.[2] We adopt a separable utility framework for donors similar to Chiang and Knight (2011) and Matějka and Tabellini (2016). An individual donor d has the following utility from donating to politician i:[3]

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

The term c_d captures the cost of donating. 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 receiving higher donations relative to newer politicians. We will focus on the case where also $\sigma_{n0}^2 > \sigma_{e0}^2$. A 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 documented by Oliver and Ha (2007).

If a politician joins Twitter then she can provide information to the donors or could send persuasive messages. The politician can send a message m to voters such that:

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

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

To highlight how joining Twitter affects donations differently for new and experienced politicians, we analyze the donations received by each type of politician with and without

[2]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. This modeling choice is in line with Durante and Knight (2012) as well as Knight and Chiang (2011).

[3]The linear utility framework is in line with (Chiang and Knight, 2011) and Durante and Knight (2012). Matějka and Tabellini (2016) adopt a more general framework where $u(\theta_i)$ is concave and differentiable.

Twitter. If the politician does not join Twitter, donor d will donate if

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

If a politician joins 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:

$$E(\theta_i|m_i) = V_{i0}m_i + V_{i\epsilon}\bar{\theta}_i$$

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

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

We define $\Delta_i \equiv E(\theta_i|m_i) - E(\theta_i)$. If $\epsilon_i > 0$, then we can establish the following proposition.

Proposition 1. *A new politician is more likely to gain from joining Twitter relative to an experienced one if her messages are more informative than those of an experienced politician (i.e., $\sigma_{e\epsilon}^2 > \sigma_{n\epsilon}^2$).*

Proof. The proof follows straight from writing out the expressions for Δ_i. $E(\theta_i|m_i) - E(\theta_i)$ is simply $\left(\frac{\sigma_{i0}^2}{\sigma_{i0}^2+\sigma_{i\epsilon}^2}\right)\epsilon_i$. This implies that $\Delta_n - \Delta_e = V_{n0}\epsilon_n - V_{e0}\epsilon_e$. The results in the proposition follow directly.

Donations and Twitter Penetration: We listed the results when 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.

3.1 Empirical Hypotheses

Based on the simple theoretical model we presented, we develop four key testable hypotheses:

(1) The total donations received by a politician increase upon adopting Twitter and sending messages.

(2) The gain from Twitter adoption is higher for new politicians compared to experienced politicians when they send more informative messages.

(3) The gain from adopting Twitter is higher for a politician who sends more informative tweets.

(4) The states with high Twitter penetration donate more to politicians adopting Twitter compared to the states with low Twitter penetration.

4 Data

Our study uses data from a variety of sources. We compile the list of politicians from the Federal Election Commission (FEC) database 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 in any of the three election cycles from 2009 to 2014.[4] For each politician, we combine weekly data on campaign contributions with data on Twitter activity. We also acquire information on the campaign expenditures, the number of media mentions of the politicians. Finally, we gather data about how Twitter usage compares to the usage of other websites in each US state, using data from comScore's online browsing panel. Summary statistics for the key variables are provided in Table A1.

Campaign Contributions and Expenditures: The data source for the political donations is the Federal Elections Committee (FEC) database which makes data on campaign contributions for each candidate publicly available.[5] We use data on the contributions to candidates, rather than to PACs or other organizations. In most of our analysis, we limit our

[4]Elections are held every two years in even-numbered years.

[5]The FEC requires candidates to identify individuals who give them more than $200 in an election cycle. Additionally, they must disclose expenditures exceeding $200 per election cycle to any individual or vendor.

attention to donations under $1000,[6] as larger donations may be motivated by other concerns than supporting a politician (e.g. lobbying efforts). The database details the amount of each contribution, its date, and the name and occupation of the donor as well as her location. For donations below $1000, the average amount of donations per week for a politician is $516 and the median amount is $500. In our analysis, we aggregate donations at politician-week level. The source of data for the campaign expenditures is the Center for Responsive Politics (opensecrets.org). The site lists the exact date for each expense item by each candidate, and we use the aggregated weekly campaign expenditures 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.[7] We combine an automated script with manual check to gather information about whether a politician has a Twitter account or not and to collect data from her account. We identify the date that the account was first activated and supplement it with data on the number of tweets and retweets, text of the tweets and the number of followers. Figure 1 demonstrates the distribution of the date of Twitter account opening for the politicians before 2014. The distribution shows that entries to Twitter take place continuously between 2009 and 2014, and there was almost no entry before 2009. Variation in entry dates reduces the concern that politicians' entry may correlate with the timing of a few specific events. Note also that most politicians adopt Twitter outside of the election periods. To reduce any concern that donations are influenced by campaign activities other than Twitter adoption, we drop Twitter accounts with "2010", "2012", "2014" or "4" (e.g., "@chip4congress", "@MCarey2012") in the handle string because use of these numbers tends to indicate that the account was started for a particular upcoming election campaign.

Twitter Penetration: We develop a Twitter penetration measure of public's use of Twitter relative to other websites by using data from comScore's online browsing panel. The panel includes all daily online activities of fifty thousand households around the US on a daily

[6] We also study donations between $1000 and $3000, in Section 6. We report the results for donations above $3000 in the Appendix.

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

basis for the period of our data.[8] The measure we employ in our analysis, aggregated at the state-year level is formally expressed as:

$$\text{Twitter Penetration}_{sy} = \left(\frac{\text{Number of Site Visits to Twitter}}{\text{Number of Visits to All Websites}}\right)_{sy}$$

Twitter penetration plays a significant role in our identification strategy.[9] To simplify back of the envelope calculations and interpretation of magnitudes, we normalize Twitter penetration such that the 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 in our list, we collect information on the number of media mentions for a window of ten weeks before and after opening an account on Twitter. We run a search for the number of times the politician's name 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 other events related to a politician's campaign around the time of opening a Twitter account which affect donations, media may also cover them, resulting in higher number of mentions. So using media mentions we can also test for the presence of simultaneous other events.

Politician Data: We collect data on 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. In our empirical analysis, we extensively use the classification of politicians into two groups: new and experienced. A politician is classified as a new politician if at the time of opening a Twitter account she had never been elected to the Congress before. If she already won an election in the past, then she is classified as an experienced politician. We present summary statistics separately for experienced and new politicians in Table A2. We will also check for heterogeneous effects of Twitter adoption by

[8] The online browsing panel does not include consumers who use mobile devices. However, recent research in marketing (Meyer and Melumad, 2016) demonstrates that consumers' use of Twitter from mobile and desktop devices are similar (approximately 60% mobile and 40% desktop computer access, with highly similar content consumption patterns in either device.)

[9] Our results are robust to an alternate Twitter penetration measure which uses the amount of time spent on Twitter relative to the amount of time spent on all other websites. Results are available upon request.

classifying the politicians as incumbents and challengers.[10] We also collect data on politicians' adoption of the most prominent competing social network, Facebook. We collected data on the dates of the first public post on Facebook for all the politicians in our list and use them as the date of adopting Facebook. We will use a dummy variable equal to one if a politician adopted Facebook before joining Twitter, and zero otherwise (for the politicians with a Twitter account).

State Characteristics: We also use data on state demographics 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 the Census database. We use data on the Republican vote share (received by George W. Bush in 2004 Presidential elections) from uselectionatlas.org. We gather information on the availability of alternative sources of information using newspaper circulation per capita data of the states from the American Association of Newspapers.

5 The Empirical Framework

The key empirical hypothesis we test claims that politicians who adopt Twitter see gains in campaign contributions.[11] Figure 2 demonstrates how political donations change in high and low Twitter penetration states, controlling for 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 are no significant pre-trends in donations to politicians between high and low Twitter penetration states before they join Twitter, but there is a visible difference after they join. Overall, Figure 2 illustrates our main point: entry to Twitter helps

[10] We prefer the new vs. experienced classification to the incumbent vs. challenger classification because an experienced politician may end up being a challenger in a future election while still benefiting from having been in the Congress before (e.g, greater name recognition, well-known policy stance, higher coverage by media, etc.). Our classification captures the short as well as the longer term incumbency advantage an experienced politician holds.

[11] We analyze two different channels through which Twitter could affect the behavior of donors. An information channel implies that opening a Twitter account allows the politicians to access a new and relatively inexpensive channel of communication with constituency. For donors who do not know about a candidate or are uninformed of her policies, this creates awareness. A persuasion channel could allow potential donors who already know the candidate to get repeated exposure to information via Twitter and persuade them to contribute more.

politicians to increase their political donations, and the support is higher in high Twitter penetration places.

To study how opening a Twitter account influences the amount of political donations received more rigorously, we use a difference-in-differences approach exploiting the precise timing of entry on Twitter.[12] The main specification we estimate is:

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

where i is the index for politicians, t is a week level time index, s is the index for state. $DonationOutcome_{it}$ will represent several ways in which we measure politician i's donation outcome in week t, including the log of total donations, number of donations, and the probability of receiving at least one donation. $Entry_{it}$ is a binary variable equal to 1 if politician i has a Twitter account in week t and 0 otherwise. $Penet_{sy}$ is the level of Twitter penetration in state s aggregated at an annual level (for year y). α_{im} is a politician-month fixed effect and $\mathbf{X_s}$ is a set of controls including average education, 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) in state s. We interact all these observed state characteristics with Twitter entry. $Expenditures_{it}$ 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. Our identification therefore comes from the precise timing of opening a Twitter account, as we effectively look at donations just before and just after Twitter entry. Note that our baseline results remain unchanged qualitatively if we replace linear time trend with week fixed effects.[13] We cluster standard errors at the level of the state, to account for

[12] Alternatively, we can estimate a difference-in-difference specification with politician rather than not politician-month and week fixed effects looking at the window of several months before and after joining Twitter, as in Figure 2. The regression results are in Table A22.

[13] Estimates with week fixed effects are provided in Tables A4 and A5 in the Appendix.

both cross-sectional and time-series variation.

Our main coefficient of interest is θ_2, corresponding to the interaction between entry on Twitter and Twitter 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 states with high or low Twitter penetration. A number of placebo specifications, reported below in subsection 6.3, ensure the credibility of our identifying assumption.[14] Figures 3, 4, and 5, for illustration, show how key alternative variables in these placebo specifications change around the time of Twitter entry in places with high or low Twitter penetration. Figures do not show significant changes in these variables, and are thus consistent with the parallel trends assumption.

6 Baseline Results, Placebos and Mechanisms

6.1 Baseline Results

We begin our analysis with the main specification (1) to evaluate the impact of joining Twitter on the aggregate weekly political donations received. The main independent variable of interest is the politician's presence on Twitter interacted with Twitter penetration. The results of the estimation are presented in Table 2, with several sets of controls included in the

[14] First, we check for other events happening simultaneously to opening a Twitter account which could drive both the Twitter entry and donations to the politicians. If a politician is involved in multiple campaign activities, we can expect to observe a spike in the campaign expenses reported to FEC 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 advertising spending. Second, we test for other events by investigating the coverage of politicians in the news media. Any report or feature on a candidate by the newspapers and blogs may influence donations or may indicate unobserved events simultaneously affecting both. Using data collected from Google News and Google Blogs, we test whether the number of mentions of a candidate increases discontinuously around the time of opening an account. Third, our identifying assumption would also be violated if the characteristics of the regions which make 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 the list of controls, interacted with a dummy for being on Twitter.

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 (0.35-0.38) as controls for campaign expenditures, time trend, and census controls interacted with joining Twitter are added. The direct effect of being on Twitter becomes insignificant once the time trend variable is introduced (column (4)). This means that in areas with no Twitter penetration, joining Twitter is not associated with an increase in donations, consistent with a prediction of our theoretical model. Columns (6) and (7) estimate Equation (1) separately for the sub-samples of new and experienced politicians. Column (6) suggests that joining Twitter is 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. We explore potential mechanisms behind these findings in subsection 6.4.

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. The average donation per candidate per week is \$1,534 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 collinear with politician-month fixed effect). Using the coefficient from column (5), the back of the envelope calculation yields \$1,534 $\times$ 0.378 $\times$ 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 of Twitter on aggregate funds raised, 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.[15]

[15] A different computational exercise could be carried out under the extreme assumption that the (information) effect of being on Twitter persists till the end of the campaign cycle. Under this stark assumption, we would have \$42,500 more donations for an average candidate, and \$49,921 more donations for an average new candidate from the time they join Twitter till the end of the election cycle.

In Table 3, we report results from testing whether similar results hold at the extensive margin, that is, if politicians receive a higher number of donations and if they are more likely to receive at least one donation in a given week post Twitter adoption. Columns (1-4) use receiving at least one donation and columns (5-8) use the number of donations as dependent variables. Findings suggest that Twitter adoption raises the likelihood of receiving a donation in a week, as well as the number of donations. In particular, the probability of receiving at least one donation per week increases by 5.1 percentage points for all politicians (column (2)), and by 8.4 percentage points for new politicians (column (3)). Experienced politicians see no significant increase in their probability (column (4)). We find similar heterogeneous effects when we consider the impact on the number of donations received in a week. New politicians joining Twitter in high penetration areas see significantly higher number of donations (column (7)) while there is no significant effect on experienced politicians (column (8)).

Next, we look what happens if we consider only larger donations. Higher ticket donors may have other reasons to donate[16], and these donors may be less susceptible to information broadcasted by the politician on Twitter. So we estimate Equation (1) this time for donations between $1,000 and $3,000. The results for aggregate donations and for the probability of receiving at least one donation are provided in Table 4. The estimates are in a similar direction to those from donations under $1000 but are smaller in magnitude. While the effect of Twitter adoption is not significant for all and experienced politicians in this donation range, coefficient is still significant for the new politicians (column (3)). The coefficient (0.57) is smaller compared to the coefficient for donations under $1,000 (given in Table 2). Although smaller in magnitude, in absolute dollars, the effect on higher ticket donations is larger since the donation amounts are higher. Repeating the back of the envelope calculation for the higher donation amounts (we multiply the average weekly sum of donations ($2,313) with 0.57 and 2.79 weeks) amounts to an increase of $3,695 additional dollars raised post Twitter adoption, or an increase of 2.1% of total donations for the average politician. Similarly, in columns (5)-(8) we report the results for the probability of receiving at least one donation between $1,000 and $3,000, which increases by 3.3 percentage points for the average politician and by 6.7 percentage points for the new politician. Thus, the results for the extensive margin are smaller

[16]For instance, business owners may donate in an effort to lobby.

in magnitude than the results for donations below $1,000, consistent with our expectations.[17] We also carry out additional tests to estimate our specifications with donations over $3,000, but do not find a significant effect of Twitter adoption.[18] Note that the declining strength of Twitter adoption for larger donations is consistent with our expectations, as larger donations may be done because donors are interested in lobbying or access to a recipient politician. Overall, the results in Tables 2-4 and in Figure 2 suggest that adoption of Twitter helps politicians raise higher total amount and number of donations, and these results hold for the new politicians but not for those who have been elected to the Congress before.

6.2 Persuasion Rates

To be able to compare the magnitudes that we uncover with other studies in the literature, we compute persuasion rates (DellaVigna and Kaplan, 2007; DellaVigna and Gentzkow, 2010). We cannot compute persuasion rates for all the followers of all politicians because we do not observe how the number of followers evolve for every politician from the time they open an account on Twitter, and we can only estimate the impact of joining Twitter within a month of Twitter entry. However, using information on the number of followers gained in the first 3-4 months after opening an account for some politicians, we can compute persuasion rates under the assumption that early number of followers are similar for politicians who just joined Twitter.[19] We observe the number of the followers for a subset of the politicians within 3 months of their account opening for two points in time: at the time of data collection by Halberstam and Knight (2016) and at the time of our own data collection. For these politicians (21% of the politicians who opened their accounts in 2012), the average number of followers gained is 104 within the first 3 months after opening a Twitter account and is 151 within the

[17] 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 A6 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.

[18] The impact of Twitter on donations between $3,000 and $5,000, and donations above $5,000, are reported in Tables A7 and A8 of the Appendix.

[19] Unfortunately, we were not lucky to have politicians who join Twitter within a month of our data collection. But we believe that the average number of followers in these early months is unlikely to change significantly. If anything, if we assume that the average number of followers is smaller than the ones we find for 3 months, our persuasion rates should be larger.

first four months. The persuasion rate calculated based on these early group of followers is likely not generalizable to the remaining parts of the population, since the characteristics of these individuals may significantly vary in terms of their interest in the politician, politics, policy issues, or engagement in technology. Further, in contrast to other studies reporting on the persuasive effects of media, we employ temporal rather than spatial variation.

To estimate the persuasion rate associated with opening a Twitter channel, we use the formula

$$f = \frac{y_t - y_c}{e_t - e_c} \times \frac{1}{1 - y_0} \times 100$$

used for reporting the persuasive effects of various media by DellaVigna and Gentzkow (2010). Here the treatment (control) group is represented by T (C), e_j is the share of group $j \in \{T, C\}$ receiving the message, y_j is the share of group j adopting the behavior of interest, and y_0 is the share that would adopt if there were no messages. DellaVigna and Gentzkow (2010) assume that where y_0 is not observed, it can be approximated by y_C. "The persuasion rate captures the effect of the persuasion treatment on the relevant behavior ($y_T - y_C$), adjusting for exposure to the message ($e_T - e_C$) and for the size of the population left to be convinced ($1 - y_0$)" (DellaVigna and Gentzkow, 2010, pg. 645).

In this study, our treatment is the entry of politician to Twitter. Similar to DellaVigna and Gentzkow (2010), we assume that $e_t - e_c$ is 100%, that is, all followers of a politician observe the treatment (entry on Twitter and the subsequent tweets within the first month). The $y_t - y_c$ is given by the coefficient from column (7) of Table 3 multiplied by the average number of donations (3.518), divided by the number of followers (151 or 104, depending on the number of months after account opening). Finally, y_0 is a counterfactual estimate for the share of donations in the absence of Twitter entry. To compute y_0, we multiply 0.352, a counterfactual estimate for donations in the absence of Twitter entry, computed by predicting donations assuming that entry to Twitter is equal to zero, by the average length of exposure (2.7), and divide it by the number of followers. [20] As before, 2.7 weeks is the average number of weeks in the month after Twitter entry. Using the numbers above, we obtain that the

[20] The number of donations all the followers would make in the absence of Twitter entry could be computed as the average realized number of donations minus the interaction coefficient multiplied by onTwitter*Twitter penetration, which corresponds to onTwitter being equal to zero (note that we should not subtract direct coefficient for Twitter entry since it is not significant).

persuasion rate (for 104 and 151 followers) is equal to:

$$f_{104} = (3.518 \times 0.155 \times 2.7/104)/(1 - .352 \times 2.7/104) = .0143 = 1.43\%$$

$$f_{151} = (3.518 \times 0.155 \times 2.7/151)/(1 - .352 \times 2.7/151) = 0.00987 = 0.98\%$$

These persuasion rates associated with opening a Twitter channel are rather at the lower end of the estimates found in the literature. It is lower than the reported persuasion rates of news media (which range from 2 p.p. to 20 p.p. for media in the United States), but it is comparable with the 1.0 p.p. persuasion rate of direct mailing (Gerber and Green, 2000) and the 0.1-1.0 p.p. persuasion rate of political advertising (Spenkuch and Toniatti, 2016). The similarity to the persuasion rate of direct mailing and advertising is not surprising, the studies of traditional media that we cite compute persuasion rate for voting, not donating, and the fraction of the public who votes is greater than the fraction of those who donate to politicians. Moreover, for donations to be reported in the FEC database, the donations from an individual must exceed $200 (either as the sum of smaller installments or in one single donation). Therefore it is likely that we are underestimating the actual persuasive power of communication via Twitter.

As a second exercise, we can compute persuasion rate for implied donations by assuming that for every donation we observe in our dataset, a fixed multiple of donations under $200 exist. For instance, if there were 2 donations below $200 for every donation above $200, our persuasion rate becomes three times the estimates given above (3.0-4.3 p.p.) and approaches the persuasion rates reported for newspaper endorsements (6 p.p. for unexpected endorsements, or 2 p.p. for expected endorsement for Chiang and Knight (2011) and the influence of TV adoption on turnout (4.4 p.p. for Gentzkow (2006)).

6.3 Placebo tests

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 assumption directly, we conduct

several tests to ensure that observations from our data are consistent with our identifying assumption.

6.3.1 Campaign Expenditures

A first potential threat to identification is the possibility of a correlation between the timing of Twitter entry and other campaign activities which can contribute to funds raised. While we do not have extremely detailed measures of campaign activities, we use campaign spending per week as a proxy. The estimates in Table 2 show that weekly campaign expenditures are strongly related to campaign contributions during the same week, indicating that this measure is indeed meaningful. To check for potential violations of the parallel trends assumption, we test if there is a spike in campaign expenditures around the date politicians start using Twitter. Table 5 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 campaign expenditures capture other activities of the politician around the same time with opening a Twitter account, this result provides a reassuring check for our identification strategy. Note that this check technically is not a placebo test, as the specification that is used is different, as we can not control for the dependent variable.

6.3.2 Political Advertising Expenditure

Another campaign activity we test is political advertising by the candidates. Similar to the test for campaign expenditures, we check if there was a spike in the political ad spending around the time a candidate joined Twitter. Table 6 shows that after including politician-month fixed effects (column (2)), joining Twitter does not predict an increase in political ad spending in neither high nor low Twitter penetration areas. Both the main effect and the interaction term are insignificant for the specification with full set of controls (column (5)). This result also holds separately for new (column (6)) and experienced politicians (column (7)), although the coefficient is negative and weakly significant at the 10% level for the experienced politicians.

Overall, we show that political ad spending does not increase with politicians joining Twitter which increases the confidence in our estimates. This and subsequent tests are traditional placebo tests, in the sense that we use exactly the same specification here as our baseline specification.

6.3.3 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[21]. Table 7 reports the results of this estimation. Overall, the estimates 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 (columns (5)-(8)), as the coefficient for Twitter entry and penetration interaction remain insignificant and are negative in some specifications.[22]

6.3.4 Twitter Entry, Twitter Penetration, and Demographics

A further concern about our identification strategy is that Twitter penetration merely serves as a proxy for income, education, or other socioeconomic characteristics of a 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 this is not the case, we test whether donations re-

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

[22] 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 data on the date each politician opened her Facebook account (if she did). We find no robust relationship between having a Facebook account before and being on Twitter and Twitter penetration interaction (please see Table A9 in the Appendix).

ceived can be explained by differential effects of entry on Twitter with different socioeconomic controls (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). We report the results in Table 8. For comparison reasons the coefficient for Twitter entry interacted with Twitter penetration (from specification in column (4) of Table 3) are reproduced in column (1). Results suggest that the interaction of being on Twitter with each of the mentioned controls is insignificant (columns (2)-(6)).[23] Therefore Twitter penetration does not seem to be a proxy for major socioeconomic characteristics of a region. Overall, while we cannot test our identifying assumption directly, the placebo checks suggest that unobserved heterogeneity and simultaneous campaign activities are not driving our key findings.

6.4 Mechanisms

The main findings suggest that a politician's adoption of Twitter causes an increase in the aggregate donations she receives. We consider two mechanisms driving donations: information and persuasion. First, adoption and activity on Twitter can help a politician to increase awareness about her candidacy and policies, which in turn can increase her support from the electorate. According to our theoretical predictions, we expect the gains to be higher for the new politicians, compared with the experienced ones, since experienced politicians' policy positions and candidacy are often better known. Alternatively, adopting Twitter and communicating through it may mainly raise donations by persuading donors who are already aware of the name and policy positions of a politician by encouraging them to donate more. Through either mechanism, the donations raised by a politician can be expected to increase after Twitter adoption. But if information is the main channel, we expect the effect to be more pronounced for the new politicians and the donations from first time donors. Similarly, gains from being on Twitter are expected to be higher in states with lower availability of alternative sources of information.

[23] We carry out additional checks to find that being on Twitter (interacted with socioeconomic controls) is not driving Twitter penetration. In addition, states with higher Twitter penetration do not see significantly more Twitter account openings. We analyze this in terms of levels and first differences of weekly Twitter penetration but find no economic or statistically significant relationship (please see Tables A10 and A11 in the Appendix).

Our baseline 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 and, in particular, with an information channel, as the marginal return to information provision through Twitter is likely lower for the experienced candidates, since their quality, experience, and policy positions are better known. For a newcomer, it is cost-effective to open an account on Twitter. 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 activity by politicians to document how differences in tweeting activity and content of tweets affect donations.

6.4.1 New vs. Previous Donors

We conjecture that a politician's presence on social media has 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 information channel, is that Twitter helps politicians to expand their 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 attracting new donors rather than just a shift in the donation amounts of repeat donors.

We split 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 that the results for new donors are in line with the information mechanism. Using Twitter in a high penetration state leads to an increase in aggregate donations received from new donors (columns (1)-(2)). Splitting the sample into new and experienced politicians shows that new donors donate more only to 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)). The probability of at least one donation from a new donor goes up by 10.3% for new politicians, but does not increase significantly for new politicians. Panel B of Table 9 shows the estimation for individuals who previously donated. For this group, we do not find an effect of being on Twitter for either new or experienced politicians. The finding is consistent with the explanation that Twitter is expanding the donor base by providing information about politicians and their policies. Twitter is influencing new rather than repeat donors who are more likely to be informed about the politician before her adoption of Twitter.

6.4.2 Influence of Other Communication Channels

Blogging on Twitter could be especially useful when voters' other channels to receive information about new politicians and their policies are limited. In this subsection, we re-estimate our benchmark specification considering newspaper circulation of the region the politician is from, separating low and high newspaper circulation regions.[24] Panel A (B) of Table 10 shows the estimates for states with newspaper circulation per capita lower (higher) than the median circulation. From Panel A, one can see that new politicians using Twitter in high penetration and low newspaper circulation areas receive a significantly higher amount in aggregate donations (columns (1)-(4)) and have a higher probability of receiving at least one donation per week (columns (5)-(8)). From Panel B, we can see that while the estimates are still significant for new politicians (columns (3) and (7)) in high newspaper circulation states, they are weaker in magnitude. The results suggest that information from social and traditional media are substitutes, and Twitter is a more effective communication channel when other means of communication such as traditional media are limited.

6.4.3 House and Senate Candidates

Another check for testing the information vs. persuasion mechanism is to compare the gains candidates running for the Senate and the House of Representatives obtain from adopting Twitter. The name recognition of candidates running for the Senate is generally higher compared to the candidates running for the House of Representatives. All states are represented

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

by two Senators but generally by a higher number of Representatives. Moreover, Senators are appointed for a six year term, compared to the two year term of a candidate elected to the House. We expect the average candidate for the House to obtain higher gains from communicating via Twitter compared to the average candidate for the Senate. We find results in line with this expectation in Table 11. While Twitter adoption in high penetration states leads to a positive and significant increase in donations for new candidates running for the House of Representatives (Panel A, columns (3) and (7)), we do not find the same effect for experienced candidates for the House (Panel A column (4) and (8)) or for the candidates to the U.S. Senate (Panel B columns (4) and (8)) elections. Again, the results are consistent with information mechanism.

6.4.4 Tweeting Activity and Tweet Content

The results indicate that Twitter activity benefits new politicians by attracting new donors, and more experienced politicians do not see a significant return from opening an account on Twitter. To document why new politicians might be attracting more donations, we analyze their tweeting activity along with the content of their tweets. We focus on the coefficient of the triple interaction term between being on Twitter, Twitter penetration, and (different measures of) tweeting activity, and consider a 25 week window around politicians' adoption of Twitter. We use the number of tweets politicians send as a measure of intensity of Twitter use and the number of retweets as a measure of popularity of their tweets.

The results from the analysis of tweeting activity are given in Table 12.[25] We find that the triple interaction term for tweets is positive and significant for the sample of new politicians (column (3)). The effect is stronger for politicians who send a high number of tweets in areas of higher Twitter penetration. The same coefficient is smaller and is not significant for the experienced politicians (column (4)). Columns (5)-(8) show that similar results hold when we use the number of retweets as a measure of popularity. New politicians who receive a higher number of retweets are likely to get a larger increase in donations in states with high Twitter penetration (column (3)), while a similar triple interaction coefficient is not significant for experienced politicians (column (4)). Analysis of the tweeting activity supports

[25] For the full table, please see Table A12 in the Appendix.

the explanation that sending more information rewards lesser known candidates at a greater rate.[26]

Next, we analyze the linguistic content of tweets. Newer politicians can be more likely to use Twitter as a channel to inform their supporters of their policy plans, or tell them to take part in the volunteering activities. To give such information, candidates may choose to add links to other websites. In Table 13, we find that about 2-3% of the total tweets include hyperlinks. We find that new politicians who include more hyperlinks receive significantly higher donations in high penetration areas (column (3)), while the coefficient is not significant for experienced politicians. Similarly, we find that politicians who use more 'inclusive' pronouns such as 'we' [27] more often receive higher donations in high Twitter penetration states, while it does not help the experienced politicians (columns (7) and (8)).[28]

Third, we carry out a sentiment analysis based on the content of the tweets by the politicians in our sample. We use a psychological approach to text analysis, more specifically the Linguistic Inquiry and Word Count methods (Pennebaker et al., 2015), which analyze the use of adjectives and pronouns to assess personality traits of individuals using these words. The scale that we use is developed by James Pennebaker and is intended to measure personal characteristics of an individual.[29] The tool generates scores about individuals' styles based on the language analysis on three dimensions: emotional, social, and thinking styles. Under emotional style upbeat, worried, angry, and depressed; under social style plugged-in, personable, arrogant, and spacy; and under thinking style analytic, sensory, and in the moment are the categories that one is scored for based on her language. While the emotional categories relate to one's positive to negative emotions, social style indicates a degree of social openness and engagement, and thinking style indicates the use of logic or senses in expression of opinions. The measure takes the recent tweets from a given Twitter handle to compute a score (between 0 to 100) of the account owner's 'social' and 'thinking' styles. In particular, we analyze how being 'plugged in' (social style, staying informed about recent news and developments) and

[26] We find that more experienced politicians, on average, send a higher number of tweets and receive a higher number of retweets (see Table A2).

[27] For the full table, please see Table A13 in the Appendix.

[28] We show that using less inclusive words (e.g., 'I') has no impact on raising donations (see Table A14 columns (5)-(8) in the Appendix).

[29] We obtain the results from AnalyzeWords.com, which uses Linguistic Inquiry and Word Count (L.I.W.C.) - choice of words, their frequency and context to determine psychological states and aspects of our personality.

'analytic' (thinking style) correlate with donation levels. We find no differential impact for politicians who score high on these traits on average. Note, however, that new politicians are, on average, more "plugged in" and more analytic than experienced politicians (see Table A2). We find that a higher "plugged in" score as a proportion of the total social style scores correlates with getting higher donations for new politicians but not the experienced ones (Table 14 columns (3) and (4)).[30] Even though new politicians score higher on analytic in thinking style, it is not associated with higher donations (See Table A14 in the Appendix). Overall, the results in this subsection are consistent with the theoretical prediction that using Twitter more informatively is associated with a greater increase in donations received following opening a Twitter account.

7 Robustness Checks and Heterogeneity

7.1 Facebook Adoption and Donations

The focus of this paper has been on Twitter in trying to address the impact of social media on the political process in general, and political donations in particular. Twitter enables quantitative analysis since information on users, their activity such as tweets is publicly available. To ensure that our Twitter results are generalizable, we collect information on when politicians in our sample joined Facebook and analyze whether Facebook adoption also leads to an increase in political donations.

Results reported in Table A3 demonstrate that our Twitter findings hold more generally. Facebook adoption leads to a statistically significant increase in the amount of weekly donations but this effect holds only for new politicians (column (3)) and not for experienced ones (column (4)). Similarly, looking at the number of donations in a week, we find that there is a significant increase in the number of donations when the politician joins Facebook and, again, this effect holds only for only new politicians (column (7)) and not experienced

[30] It is also interesting to note that other social styles do not correlate with donations. We also analyze how emotional styles correlate with donations, focusing on the impact of 'worried emotional style'. A worried style does not correlate with donations raised for new politicians but it is negatively correlated for experienced politicians (see Table A15 in the Appendix).

ones (column (8)).[31] Overall, these results suggest that our Twitter estimates have external validity and can be viewed more generally as representative of the impact of social media on political donations. Facebook results are somewhat weaker, however, maybe due to the fact that Twitter with its followers structure is more often used for political discussions.

7.2 Heterogeneous Effects Between Democrats and Republicans

Republican and Democratic voters have traditionally differed in demographic characteristics. Democratic voters are generally 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 use, implying that candidates registered with the Democratic Party may have higher returns from adopting Twitter because the medium appeals to their constituents. We test whether Twitter has an asymmetric effect on candidates from the two parties.

Panel A of Table A16 (in the Appendix) shows the estimates for the Democrats while Panel B demonstrates the effects for the Republicans. In Panel A, one can see that new Democratic politicians using Twitter in higher penetration areas receive a significantly higher amount in aggregate donations (columns (1)-(4)) and have higher probability of receiving at least one donation per week (columns (5)-(8)). But experienced Democratic politicians do not show a gain. In Panel B, the effects hold for new Republican politicians (columns (3) and (7)) as well, but are weaker quantitatively. Overall, these results suggest that Twitter adoption has heterogeneous effects across the two party candidates and Democrats gain substantially more from it, possibly because of the demographic differences between the target audiences of the two parties.

7.3 Within and Out of State Donations

An implication of using a state level Twitter penetration measure is that we expect the residents of a state to be the ones predominantly donating to the candidates running for an office from their state. To validate the use of the within state Twitter penetration measure, we

[31] We do not find a significant impact on the probability on donating with p-values of 0.16. Results available upon request.

compare if donations coming from residents within and out of state respond differently to a politician's Twitter entry. The results in Tables A17 and A18 demonstrate how this intuition is supported by the data. Table A17 shows that the within state estimates are statistically significant and positive across all politicians (columns (1)-(5)) with a stronger effect for those who are new (column (6)). Quantitatively, the magnitudes are similar to the baseline results. The estimates are again insignificant for the experienced politicians (column (7)). When the donations from donors located in another state than the politician's own are analyzed, we find that the impact of Twitter entry is statistically insignificant for all and the experienced politicians (columns (1)-(5), and (7)) and marginally significant (10% level) for new politicians, with the coefficients substantially smaller for out-of-state compared to in-state donations.

7.4 Twitter Entry, Donations, and Followers

To test for the overlap between the users on Twitter, we match the names of the donors to a politician to the names of her followers in Twitter. Using first and last names along with information on geographical locations, we are able to achieve a match rate of 3.65%. While this rate is seemingly low, it is comparable to the match rates in other studies of Twitter users (e.g., 10% in Barbera (2015)). We acknowledge that matching is not perfect, but we expect it to only introduce attenuation bias to our results. To assess the impact of joining Twitter and whether the donations came from followers of politicians on Twitter, we focus on candidate-weeks which have donations from both followers and non followers.

Table A19 shows that followers have a relatively larger probability of making a donation after a candidate joins twitter (columns (1)-(4)), and followers give proportionately more after the politician joins Twitter relative to other non-follower donors (columns (5)-(8)). The share of the number of donations coming from followers increases by approximately 7% which is in line with our baseline results. While these results are still speculative, the direction of the results is in line with our expectations.

7.5 Excluding the Year 2009 and Campaign Periods

Our data highlights that a disproportionate number of Twitter accounts were opened in 2009. While including the politician-month fixed effects and a week time trend (or week fixed effects)

account for any idiosyncrasies of a particular time period, we would like to test if our estimates are driven by only one year's worth of data. We exclude the accounts started in 2009 and re-estimate our baseline specification. Table A20 in the Appendix shows that the results remain similar to our baseline estimates qualitatively and quantitatively. Being on Twitter in a high penetration state leads to higher aggregate donations (columns (1) to (4)) as well as a higher probability of receiving at least one donation per week (columns (5) to (8)). Again, the effects hold only for new politicians and not the experienced ones.

While the placebo checks we reported rule out the possibility of simultaneous campaign events driving our results, as another test we run our specification using only data from off-election years and the months over which a politician is less likely to be actively involved in campaign efforts. Elections take place in even numbered years (2010, 2012 and 2014 in our sample), so it is likely that in the first half of each of the odd numbered years (2009, 2011, 2013) campaign activities would be limited. We re-estimate our diff-in-diff specifications using data only from the first six months of 2009, 2011 and 2013. In Table A21 in the Appendix, we find that even focusing 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)) and remains insignificant for those who are experienced (columns (3) and (6)). For all politicians estimates are insignificant (columns (1) and (4)).

7.6 Week of Month Fixed Effects and Quadratic Time Trend

Our estimates capture the effect of a politician's Twitter adoption on donations in the month of opening the account. In an additional robustness check we control for the heterogeneity in timing of donations across the weeks within this month. This test is important since donations may be clustered towards the end of the month for reasons such as individuals receiving their paychecks in the last week of the month. In Tables A22 and A23 we report results of our baseline specifications with politician and week fixed effects and week of the month fixed effects. The results are in line with our baseline estimates qualitatively and quantitatively for aggregate donations (columns (1)-(4)) and the probability of receiving donations (columns (5)-(8)).

We also report results from the specification where we interact being on Twitter with

a linear and quadratic time trend. These can capture time varying characteristics, beyond those we accounted for by interacting Twitter adoption with time invariant socio-demographic characteristics. Since our Twitter penetration measure is at state-year level, we interact Twitter adoption with annual linear and quadratic time trends. The results in Table A24 indicate that these results are in line with the baseline estimates for new (columns (3) and (7)) and experienced politicians (columns (4) and (8)).

8 Conclusion

Electoral campaigns in the past years have seen a significant change in the communication channels used by the candidates to reach out to the electorate (Andrews and Ballhaus, 2015). A notable change during this period was the intensified use of social media platforms to reach out to and inform voters, partially eliminating dependence on traditional media outlets such as newspapers and television. The essential question is whether the use of social media by politicians fundamentally alters 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 social media (Twitter, Facebook) can help her to attract new donations for new politicians. Overall, results imply that social media can help to democratize electoral politics by reducing the barriers for new politicians to raise money from the public.

Many avenues of future research lie at the intersection of adoption of new communication technologies and political outcomes. Future studies may 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 whether political advertising and the use of social media are complements or substitutes in delivering information about the candidates and their policies to voters. Further, a unique feature of social media is two-way communication, which may allow politicians to directly listen to citizens' concerns and respond by policy proposals. Our results are not directly related to political polarization, but since new politicians are likely to avoid strong statements, they can explain why social media does not seem to be associated with much higher political polarization (Gentzkow et al., 2011; Halberstam and Knight, 2016).

Finally, 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 the 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.

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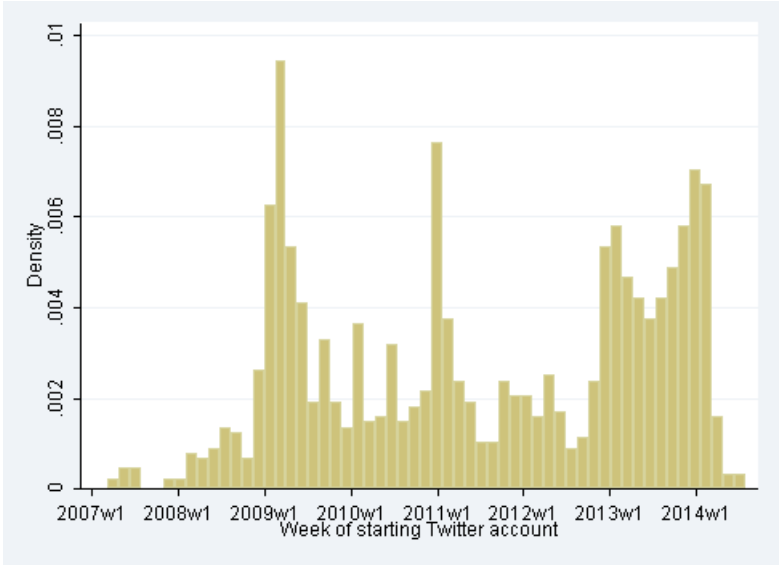

Figure 1: Dates (week) of Opening an Account on Twitter

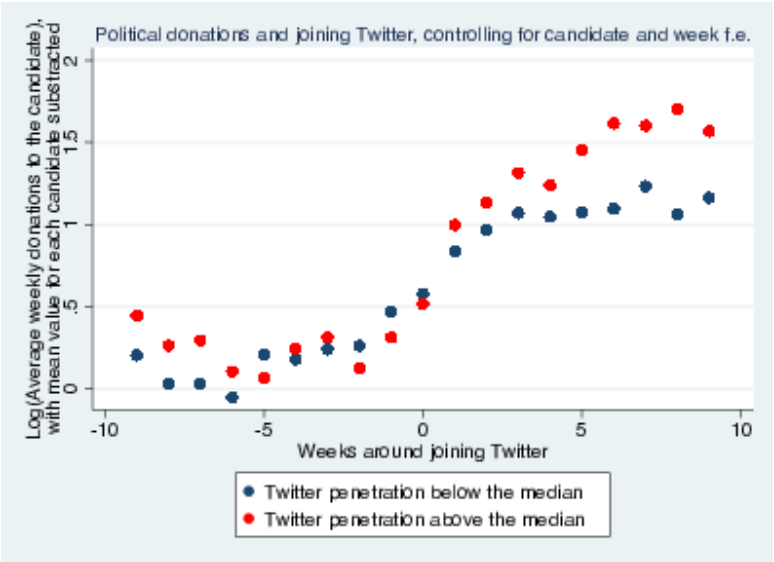

Figure 2: Donations and Twitter Penetration

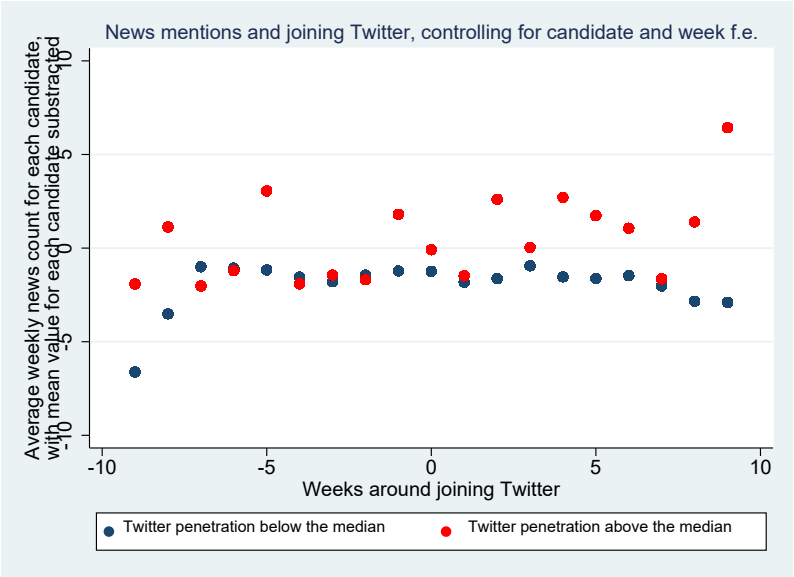

Figure 3: Number of News Mentions and Twitter Penetration

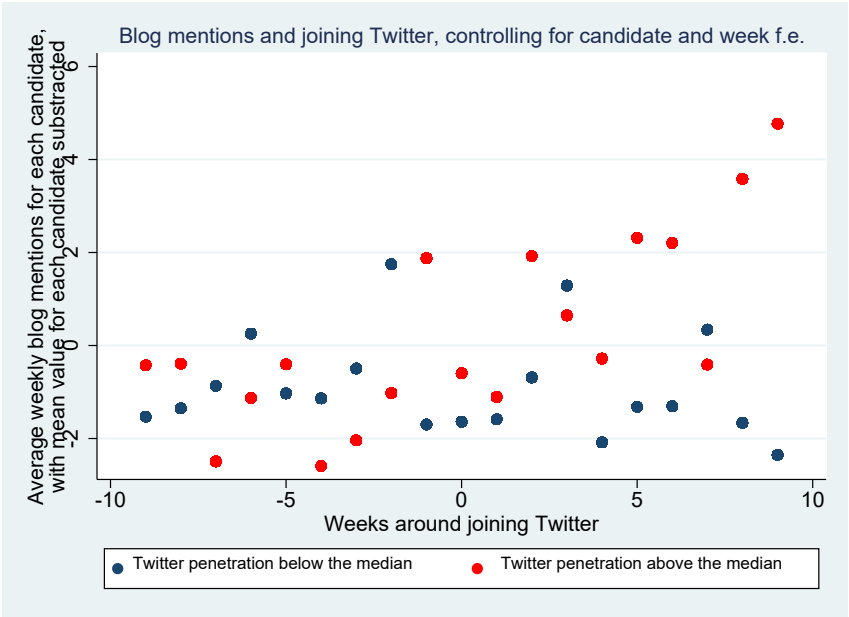

Figure 4: Number of Blog Mentions and Twitter Penetration

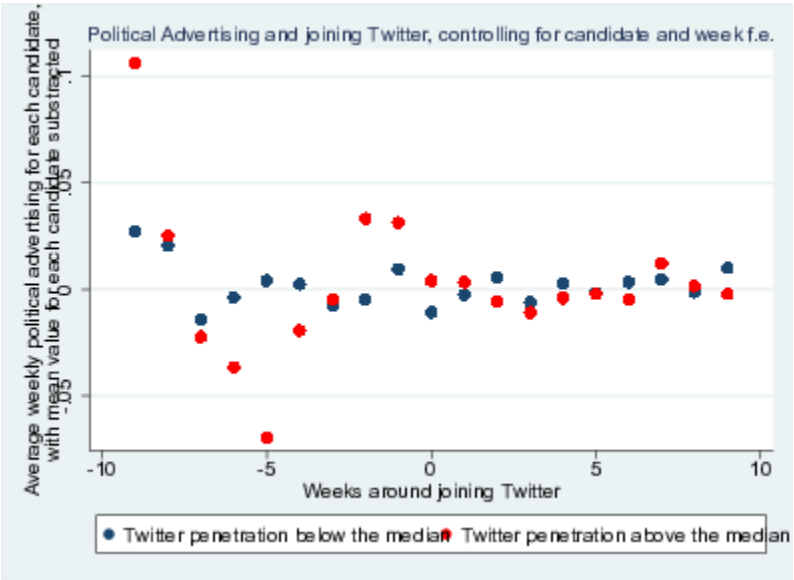

Figure 5: Political Advertising and Twitter Penetration

Table 1: Summary Statistics: All Politicians

Variable	Observations	Mean	Std. Dev.	Min	Max
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: Joining Twitter and Aggregate Donations: Baseline Estimates

	Log (Aggregate donations)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All Politicians					New	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

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 donations in a week. Columns (1) - (5) include all politicians while column (6) includes only new and column (7) only the experienced politicians. State level baseline controls 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 3: Twitter Adoption, Probability of Receiving at least one Donation & Number of Donations

	Probability of Receiving at least One Donation				Number of Donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration	0.047**	0.051**	0.084***	-0.014	0.0563	0.0633	0.155***	-0.107
	(0.019)	(0.019)	(0.024)	(0.034)	(0.0411)	(0.0418)	(0.0450)	(0.0701)
on Twitter	0.021	0.023	-0.476	0.876	0.0469*	0.158	-0.931	2.092*
	(0.014)	(0.343)	(0.451)	(0.617)	(0.0276)	(0.546)	(0.708)	(1.147)
Log (campaign expenditure)	0.011***	0.011***	0.015***	0.009***	0.0265***	0.0265***	0.0353***	0.0232***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.00101)	(0.00101)	(0.00208)	(0.000973)
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	0.788	0.788	0.847	0.752	0.840	0.840	0.902	0.802

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 probability of receiving at least one donation in a week in columns (1) - (4) while it is the total number of donations in a week in columns (5)-(8). Columns (1) - (2) and (5)-(6) include all politicians while columns (3) and (6) includes only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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 (Donations between $1000 and $3000)

	Log(Aggregate donations)				At least one donation per week			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	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		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	0.759	0.759	0.826	0.722	0.727	0.727	0.791	0.690

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 donations in columns (1)-(4) and the probability of getting at least 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 5: Joining Twitter and Campaign Expenditures

	Log (campaign expenditures)					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		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 on Twitter				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

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 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 6: Joining Twitter and Political Advertising

	Log (Political Advertising)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All Politicians					New	Experienced
on Twitter x Twitter penetration	-0.068***	-0.052	-0.053	-0.053	-0.060	0.025	-0.218*
	[0.021]	[0.037]	[0.038]	[0.038]	[0.038]	[0.054]	[0.126]
on Twitter	0.065***	0.033	0.030	0.014	-0.802	-1.200	0.075
	[0.017]	[0.026]	[0.026]	[0.026]	[0.592]	[0.790]	[0.674]
Log (campaign expenditure)			0.008***	0.008***	0.008***	0.010***	0.008***
			[0.001]	[0.001]	[0.001]	[0.002]	[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	0.000	0.813	0.814	0.814	0.814	0.830	0.802

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 donations in a week. Columns (1) - (5) include all politicians while column (6) includes only new and column (7) only the experienced politicians. State level baseline controls 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

	Number of News Mentions				Number of Blog Mentions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	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

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 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) include only new and columns (4) and (8) have the experienced politicians. State level baseline controls 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 8: Demographic Characteristics and Donations

	Log (aggregate donations per week)					
VARIABLES	(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 x share of rich			-0.031			
			(0.083)			
on Twitter x share of those with college education				-2.175		
				(1.839)		
on Twitter x vote share of Bush in 2004					0.164	
					(0.858)	
on Twitter x share of African Americans						0.279
						(1.024)
on Twitter	0.931	0.276	1.289	-0.00722	0.191	0.374***
	(0.601)	(0.224)	(1.390)	(0.423)	(0.142)	(0.129)
Log(campaign expenditures)	0.0906***	0.0906***	0.0906***	0.0906***	0.0906***	0.091***
	(0.00408)	(0.00408)	(0.00408)	(0.00408)	(0.00408)	(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

Note: 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: Donations from New and Repeat donors

Panel A. Donations from new donors.

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	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	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 repeat donors.

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	-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	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

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 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) include all politicians while columns (3) and (7) include only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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: Donations and Newspaper Circulation

Panel A. Donations in Low Circulation States

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(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

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(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

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 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) include all politicians while columns (3) and (7) include only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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: Joining Twitter and Donations: House vs. Senate Candidates

Panel A. Donations to House Candidates

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.375**	0.428**	0.754***	-0.199	0.048**	0.055**	0.091***	-0.016
	[0.168]	[0.171]	[0.181]	[0.337]	[0.022]	[0.023]	[0.025]	[0.046]
on Twitter	0.130	0.278	-4.415	7.088*	0.019	-0.013	-0.700	0.993
	[0.108]	[2.706]	[4.028]	[4.123]	[0.015]	[0.380]	[0.552]	[0.613]
Log (campaign expenditures)	0.090***	0.090***	0.125***	0.079***	0.011***	0.011***	0.016***	0.009***
	[0.004]	[0.004]	[0.009]	[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	450,979	450,979	186,308	264,671	450,979	450,979	186,308	264,671
R-squared	0.809	0.809	0.866	0.776	0.779	0.779	0.831	0.745

Panel B. Donations to Senate Candidates

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
on Twitter x Twitter penetration	0.187	0.173	0.405	0.093	0.038	0.035	0.054	0.044
	[0.288]	[0.278]	[0.394]	[0.399]	[0.039]	[0.038]	[0.059]	[0.055]
on Twitter	0.294	2.487	5.479	-3.685	0.030	0.258	0.814	-0.877
	[0.215]	[5.123]	[5.662]	[10.512]	[0.028]	[0.758]	[0.794]	[1.475]
Log (campaign expenditures)	0.095***	0.095***	0.108***	0.077***	0.010***	0.010***	0.012***	0.007***
	[0.010]	[0.010]	[0.012]	[0.016]	[0.001]	[0.001]	[0.002]	[0.002]
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	114,785	114,785	50,392	64,393	114,785	114,785	50,392	64,393
R-squared	0.867	0.867	0.926	0.826	0.824	0.824	0.893	0.779

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 donation in a week for House candidates in Panel A and for the Senate 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 12: Politicians' Tweets and Retweets

	Log (aggregate donations)							
	(1)	2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration x log(# of tweets)	0.603	0.465	4.285**	0.262				
	(0.546)	(0.566)	(1.644)	(0.623)				
on Twitter x Twitter penetration x log(# of retweets)					0.111	-0.0271	3.087***	0.0192
					(0.365)	(0.338)	(0.749)	(0.390)
on Twitter	0.371***	0.391	-3.710	7.392	0.423***	0.532	-3.473	7.416
	(0.103)	(2.422)	(3.260)	(4.481)	(0.104)	(2.455)	(3.327)	(4.498)
on Twitter x Twitter penetration	0.399**	0.417***	0.748***	-0.199	0.363**	0.379**	0.697***	-0.213
	(0.150)	(0.145)	(0.175)	(0.253)	(0.149)	(0.145)	(0.171)	(0.259)
Log(campaign expenditure)		0.105***	0.119***	0.0916***		0.105***	0.119***	0.0916***
		(0.00720)	(0.0124)	(0.00954)		(0.00718)	(0.0124)	(0.00954)
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	78,107	78,082	46,964	31,118	78,107	78,082	46,964	31,118
R-squared	0.792	0.797	0.843	0.727	0.792	0.797	0.843	0.727

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 donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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: Tweet Content: Number of URLs and Number of Use of Word "We"

	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration x log(# of tweets with links)	-0.544	-1.207	13.45***	-1.198				
	(1.065)	(1.063)	(1.545)	(1.201)				
on Twitter x Twitter penetration x log(# of tweets with 'we')					1.778	1.986	73.56***	-9.190
					(11.30)	(11.33)	(2.590)	(6.633)
on Twitter x Twitter penetration	0.382**	0.399***	0.719***	-0.196	0.360**	0.377**	0.693***	-0.212
	(0.150)	(0.145)	(0.171)	(0.258)	(0.150)	(0.145)	(0.171)	(0.258)
on Twitter	0.398***	0.502	-3.395	7.299	0.432***	0.590	-3.296	7.322
	(0.104)	(2.422)	(3.314)	(4.478)	(0.105)	(2.432)	(3.301)	(4.494)
log(campaign expenditure)		0.105***	0.119***	0.0917***		0.106***	0.119***	0.0915***
		(0.00721)	(0.0124)	(0.00956)		(0.00718)	(0.0124)	(0.00952)
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	78,107	78,082	46,964	31,118	78,107	78,082	46,964	31,118
R-squared	0.792	0.797	0.843	0.727	0.792	0.797	0.843	0.727

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 donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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: Tweet Sentiment: "Plugged In"

	Log (aggregate donations)			
	(1)	(2)	(3)	(4)
VARIABLES	All	All	New	Experienced
on Twitter x Twitter penetration x log(plugged in score)	0.612	0.565	0.632*	0.553
	(0.386)	(0.384)	(0.370)	(0.697)
on Twitter x log('plugged in' score)	0.168	0.190	0.0134	0.373
	(0.363)	(0.367)	(0.312)	(0.741)
on Twitter x Twitter penetration	1.176*	1.128*	1.528**	0.604
	(0.625)	(0.631)	(0.622)	(1.099)
on Twitter	0.700	2.586	-2.316	9.806**
	(0.556)	(2.572)	(3.463)	(4.586)
log(campaign expenditure)		0.107***	0.121***	0.0937***
		(0.00742)	(0.0131)	(0.00987)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes
Time trend		Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes
Observations	70,260	70,239	41,999	28,240
R-squared	0.790	0.794	0.845	0.720

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 donations in a week. Columns (1)-(2) include all politicians while column (3) includes only new and column (4) only the experienced politicians. State level baseline controls 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

Supplementary Tables

Table A1: 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 A2: Summary Statistics: New and Experienced Politicians

Variable	N	Mean	Std. Dev.	Min	Max	N	Mean	Std. Dev.	Min	Max	Difference
			New					Experienced			(Experienced-New)
Log(Aggregate Donations)	1,230	1.34	1.50	0	8.30	604	3.30	2.32	0	9.48	1.96 (0.90)***
Probability of Donations	1,230	0.17	0.18	0	0.89	604	0.41	0.28	0	0.99	0.24 (0.10)***
Log(Campaign Expenditure)	1,230	1.59	1.86	0	8.42	604	4.46	3.20	0	11.24	2.87 (0.11)***
Num. of News Mentions	1,230	4.93	37.77	0	946.85	604	30.41	526.51	0	11281.43	18.83 (13.17)*
Num. of Blog Mentions	1,230	3.91	36.43	0	780.52	604	18.77	310.72	0	6641.90	10.81 (7.85)*
Facebook Account Before	1,230	0.01	0.09	0	0.98	604	0.05	0.20	0	1	0.03 (0.006)***
Log(Num. of Tweets)	1,230	0.09	0.26	0	1.89	604	0.13	0.32	0	1.98	0.03 (0.01)**
Log(Num. of Retweets)	1,230	0.09	0.30	0	2.50	604	0.18	0.54	0	4.91	0.08 (0.01)***
Log(Num. of Favorites)	1,230	0.02	0.11	0	1.16	604	0.09	0.32	0	3.66	0.06 (0.01)***
Log(Proportion of URLs)	1,230	0.02	0.07	0	0.50	604	0.03	0.09	0	0.52	0.009 (0.003)*
Log(Proportion of Words)	1,230	0.003	0.008	0	0.09	604	0.004	0.01	0	0.66	0.001 (0.0004)***
Log(Proportion of 'I')	1,230	0.01	0.001	0	0.32	604	0.02	0.002	0	0.27	0.005 (0.002)***
Log(Proportion of 'We')	1,230	0.003	0.009	0	0.07	604	0.004	0.01	0	0.08	0.0008 (0.0004)**
'Plugged In' Score	998	51.59	18.66	0	98	647	54.17	19.62	0	100	-2.579 (0.961)***
'Analytic' Score	998	40.01	15.84	8	100	647	40.78	18.24	8	100	0.77 (0.874)

Table A3: Facebook Adoption, Amount of Donations and the Number of Donations

	Log Aggregate Donations				Number of Donations			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Facebook x Facebook penetration	0.609	0.629	1.254*	0.0899	0.216	0.221	0.376**	0.111
	(0.572)	(0.570)	(0.738)	(0.739)	(0.152)	(0.152)	(0.150)	(0.225)
on Facebook	0.360	0.334	-0.120	0.544	0.117	0.112	-0.0292	0.177
	(0.654)	(0.651)	(0.902)	(0.862)	(0.144)	(0.144)	(0.163)	(0.199)
Log (campaign expenditure)	0.090***	0.090***	0.121***	0.079***	0.026***	0.026***	0.035***	0.023***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.001)	(0.001)	(0.002)	(0.0009)
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	0.823	0.823	0.885	0.787	0.840	0.840	0.902	0.802

Note: 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 in columns (1) - (4) while it is the total number of donations in a week in columns (5)-(8). Columns (1) - (2) and (5)-(6) include all politicians while columns (3) and (6) includes only new and columns (4) and (8) only the experienced politicians. State level baseline controls interacted with the politician being on Facebook 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 A4: Joining Twitter and Aggregate Donations: Baseline Estimates with Week Fixed Effects

	Log (Aggregate donations)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES			All Politicians			New	Experienced
on Twitter x Twitter penetration	-0.340***	0.359**	0.353**	0.354**	0.374**	0.520***	0.155
	(0.117)	(0.148)	(0.147)	(0.146)	(0.142)	(0.172)	(0.238)
on Twitter	1.312***	0.435***	0.406***	0.148	0.915	-2.934	7.154
	(0.116)	(0.104)	(0.103)	(0.0978)	(2.430)	(3.280)	(4.280)
Log (campaign expenditure)			0.0941***	0.0852***	0.0852***	0.118***	0.0693***
			(0.00407)	(0.00426)	(0.00426)	(0.00741)	(0.00441)
Politician-Month Fixed Effects		Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects				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	0.825	0.825	0.886	0.791

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 donations in a week. Columns (1) - (5) include all politicians while column (6) includes only new and column (7) only the experienced politicians. State level baseline controls 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 A5: Joining Twitter and the Probability and Number of Donations with Week Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration	0.0478**	0.0506**	0.0665***	0.0256	0.0564	0.0600	0.0927**	0.0137
	(0.0194)	(0.0193)	(0.0241)	(0.0325)	(0.0413)	(0.0422)	(0.0455)	(0.0664)
on Twitter	0.0178	0.0430	-0.452	0.846	0.0509*	0.250	-0.823	1.978*
	(0.0140)	(0.345)	(0.447)	(0.597)	(0.0279)	(0.546)	(0.719)	(1.141)
Log (campaign expenditure)	0.0103***	0.0103***	0.0144***	0.00836***	0.0245***	0.0245***	0.0339***	0.0196***
	(0.000618)	(0.000617)	(0.00103)	(0.000632)	(0.00106)	(0.00106)	(0.00199)	(0.00103)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	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	0.788	0.788	0.847	0.752	0.840	0.840	0.902	0.802

Note: 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 at least one donation in a week in columns (1) - (4) while it is the total number of donations in a week in columns (5)-(8). Columns (1) - (2) and (5)-(6) include all politicians while columns (3) and (6) includes only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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 A6: Joining Twitter, Aggregate Donations, and Different Window Size Specifications

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

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. Baseline controls 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 A7: Joining Twitter and Aggregate Donations ($3000-$5000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	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

Note: 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 at least one donation in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only the new and columns (4) and (8) only the experienced politicians. State level baseline controls 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 A8: Joining Twitter and Aggregate Donations (Above $5000)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	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

Note: 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 at least one donation in columns (5)-(8). Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only the new and columns (4) and (8) only the experienced politicians. State level baseline controls 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 A9: Joining Twitter and Facebook Accounts

	Joined Facebook Before						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	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

Note: 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) include all politicians while column (6) includes only the new and column (7) only the experienced politicians. State level baseline controls 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 A10: Twitter Entry, Demographics, and Twitter Penetration: Levels

	Twitter Penetration: Levels					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
on Twitter	-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 x share of rich			2.27e-05			
			(3.15e-05)			
on Twitter x share of those with college education				0.0002		
				(0.0006)		
on Twitter x vote share of Bush in 2004					0.0001	
					(0.0002)	
on Twitter x share 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 A11: Twitter Entry, Demographics and Twitter Penetration: First Differences

	Twitter Penetration: First Difference					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
on Twitter	-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 x share of rich			-1.63e-05			
			(4.30e-05)			
on Twitter x share of those with college education				0.0008		
				(0.0009)		
on Twitter x vote share of Bush in 2004					0.0003	
					(0.0004)	
on Twitter x share 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

Note: 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 A12: Politician Tweets and Retweets: Full Table

	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
onTwitter x Twitter penetration x log(# of tweets)	0.374	0.474	0.285	0.884				
	(0.652)	(0.663)	(0.739)	(1.111)				
onTwitter x Twitter penetration x log(# of retweets)					-1.108	-1.509	-2.332	-2.227
					(1.717)	(1.714)	(3.611)	(2.412)
onTwitter x log(# of tweets)	-0.637	-0.459	-1.902***	-0.294				
	(0.628)	(0.671)	(0.358)	(0.757)				
onTwitter x log(# of retweets)					-0.0651	0.0728	-1.502***	-0.0338
					(0.454)	(0.414)	(0.373)	(0.473)
Twitter penetration x log(# of tweets)	-0.808	-0.671	-4.433**	-0.368				
	(0.553)	(0.573)	(1.680)	(0.620)				
Twitter penetration x log(# of retweets)					-0.327	-0.170	-3.308***	-0.0977
					(0.340)	(0.313)	(0.237)	(0.362)
log(# of tweets)	0.946	0.755	2.229***	0.435				
	(0.637)	(0.680)	(0.366)	(0.753)				
log(# of retweets)					0.398	0.222	1.894***	0.145
					(0.409)	(0.373)	(0.141)	(0.429)
onTwitter	0.0138	1.155	-3.777	9.125*	0.424***	0.555	-3.309	7.308
	(0.467)	(2.724)	(3.618)	(4.586)	(0.104)	(2.431)	(3.296)	(4.511)
onTwitter x Twitter penetration	0.707	0.838	0.936	0.757	0.363**	0.380**	0.691***	-0.209
	(0.638)	(0.653)	(0.745)	(1.053)	(0.150)	(0.145)	(0.171)	(0.261)
Log(campaign expenditure)		0.106***	0.121***	0.0922***		0.106***	0.119***	0.0917***
		(0.00749)	(0.0131)	(0.00975)		(0.00718)	(0.0124)	(0.00954)
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	70,954	70,932	42,405	28,527	78,107	78,082	46,964	31,118
R-squared	0.789	0.794	0.844	0.720	0.792	0.797	0.843	0.727

Note: 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 A13: Tweet Content: Number of URLs and Number of Use of Word "We": Full

	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration x log(# of tweets with links)	-0.544	-1.207	13.45***	-1.198				
	(1.065)	(1.063)	(1.545)	(1.201)				
on Twitter x Twitter penetration x log(# of tweets with 'we')					1.778	1.986	73.56***	-9.190
					(11.30)	(11.33)	(2.590)	(6.633)
onTwitter x log(# of tweets with links)	0.998	1.521	-4.329***	1.480				
	(1.276)	(1.376)	(0.550)	(1.588)				
onTwitter x log(# of tweets with 'we')					-0.352	-0.334	-45.61***	10.14
					(11.05)	(11.08)	(0.923)	(7.069)
Twitter penetration x log(# of tweets with links)	-0.119	0.478	-14.33***	0.623				
	(1.029)	(1.031)	(0.811)	(1.067)				
Twitter penetration x log(# of tweets with 'we')					-2.190	-2.370	-71.65***	9.093
					(11.39)	(11.43)	(0.222)	(6.628)
log(# of tweets with links)	-0.0547	-0.599	5.391***	-0.768				
	(1.220)	(1.331)	(0.318)	(1.371)				
log(# of tweets with 'we')					0.993	0.950	45.71***	-10.16
					(11.12)	(11.16)	(0.0485)	(7.058)
on Twitter x Twitter penetration	0.382**	0.399***	0.719***	-0.196	0.360**	0.377**	0.693***	-0.212
	(0.150)	(0.145)	(0.171)	(0.258)	(0.150)	(0.145)	(0.171)	(0.258)
on Twitter	0.398***	0.502	-3.395	7.299	0.432***	0.590	-3.296	7.322
	(0.104)	(2.422)	(3.314)	(4.478)	(0.105)	(2.432)	(3.301)	(4.494)
log(campaign expenditure)		0.105***	0.119***	0.0917***		0.106***	0.119***	0.0915***
		(0.00721)	(0.0124)	(0.00956)		(0.00718)	(0.0124)	(0.00952)
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	78,107	78,082	46,964	31,118	78,107	78,082	46,964	31,118
R-squared	0.792	0.797	0.843	0.727	0.792	0.797	0.843	0.727

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 donations in a week. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (4) and (8) only the experienced politicians. State level baseline controls 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 A14: Politician Tweets: Sentiment analysis and Tweet Content

	Log (aggregate donations)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
onTwitter x Twitter penetration x log('analytic' score)	0.374	0.474	0.285	0.884				
	(0.652)	(0.663)	(0.739)	(1.111)				
onTwitter x Twitter penetration x log(# of tweets with 'I')					-1.108	-1.509	-2.332	-2.227
					(1.717)	(1.714)	(3.611)	(2.412)
onTwitter x log('analytic' score)	-0.412	-0.441	-0.361	-0.620				
	(0.445)	(0.436)	(0.562)	(0.746)				
onTwitter x log(# of tweets with 'I')					2.023	2.474	1.643*	3.335
					(1.748)	(1.845)	(0.843)	(2.663)
Twitter penetration x log(# of tweets with 'I')					1.030	1.389	3.444	1.936
					(1.685)	(1.698)	(2.960)	(2.345)
log(#I)					-1.724	-2.180	-1.843**	-2.795
					(1.699)	(1.816)	(0.766)	(2.536)
onTwitter	0.0138	1.155	-3.777	9.125*	0.424***	0.555	-3.309	7.308
	(0.467)	(2.724)	(3.618)	(4.586)	(0.104)	(2.431)	(3.296)	(4.511)
onTwitter x Twitter penetration	0.707	0.838	0.936	0.757	0.363**	0.380**	0.691***	-0.209
	(0.638)	(0.653)	(0.745)	(1.053)	(0.150)	(0.145)	(0.171)	(0.261)
Log(campaign expenditure)		0.106***	0.121***	0.0922***		0.106***	0.119***	0.0917***
		(0.00749)	(0.0131)	(0.00975)		(0.00718)	(0.0124)	(0.00954)
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	70,954	70,932	42,405	28,527	78,107	78,082	46,964	31,118
R-squared	0.789	0.794	0.844	0.720	0.792	0.797	0.843	0.727

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 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 A15: Tweet Sentiment: 'Worried'

	Log (aggregate donations)			
	(1)	(2)	(3)	(4)
VARIABLES	All	All	New	Experienced
on Twitter x Twitter penetration x log('worried' score)	-0.458	-0.453	0.479	-1.674*
	(0.542)	(0.521)	(0.568)	(0.838)
onTwitter x log('worried' score)	0.116	0.108	-0.309	0.646
	(0.358)	(0.346)	(0.352)	(0.723)
on Twitter x Twitter penetration	-0.469	-0.437	1.439	-3.033**
	(0.870)	(0.842)	(0.942)	(1.409)
on Twitter	0.651	1.579	-3.662	9.939**
	(0.588)	(2.833)	(3.442)	(4.782)
log(campaign expenditure)		0.106***	0.121***	0.0924***
		(0.00750)	(0.0131)	(0.00974)
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes
Time trend		Week	Week	Week
Baseline controls x on Twitter		Yes	Yes	Yes
Observations	70,954	70,932	42,405	28,527
R-squared	0.789	0.794	0.844	0.720

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 donations in a week. Columns (1)-(2) include all politicians while column (3) includes only new and column (4) only the experienced politicians. State level baseline controls 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 A16: Joining Twitter and Donations: Democrats vs. Republicans

Panel A. Donations to Democrats.

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(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.

	Log (aggregate donations)				At least one donation per week			
	All	All	New	Experienced	All	All	New	Experienced
VARIABLES	(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

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 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 A17: Joining Twitter and Within State Donations

	Log (Aggregate donations)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All Politicians					New	Experienced
on Twitter x Twitter penetration	-0.298**	0.347**	0.335**	0.332**	0.342**	0.591***	-0.126
	[0.112]	[0.142]	[0.143]	[0.143]	[0.141]	[0.153]	[0.292]
on Twitter	1.115***	0.406***	0.383***	0.156	0.547	-2.732	6.147
	[0.100]	[0.108]	[0.108]	[0.106]	[2.305]	[2.990]	[3.863]
Log (campaign expenditure)			0.085***	0.082***	0.082***	0.122***	0.067***
			[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	543,504	543,504	543,305	543,305	543,305	225,866	317,439
R-squared	0.016	0.794	0.796	0.797	0.797	0.866	0.758

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 donations in a week. Columns (1) - (5) include all politicians while column (6) includes only new and column (7) only the experienced politicians. State level baseline controls 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 A18: Joining Twitter and Outside the State Donations

	Log (Aggregate donations)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	All Politicians					New	Experienced
on Twitter x Twitter penetration	-0.220**	0.094	0.094	0.092	0.132	0.391*	-0.285
	[0.084]	[0.180]	[0.181]	[0.180]	[0.180]	[0.204]	[0.221]
on Twitter	0.825***	0.393***	0.364***	0.091	0.441	-1.301	3.282
	[0.080]	[0.121]	[0.124]	[0.122]	[1.787]	[2.542]	[3.498]
Log (campaign expenditure)			0.059***	0.055***	0.055***	0.058***	0.054***
			[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	500,760	500,760	500,559	500,559	500,559	204,734	295,825
R-squared	0.011	0.709	0.710	0.713	0.713	0.801	0.670

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 donations in a week. Columns (1) - (5) include all politicians while column (6) includes only new and column (7) only the experienced politicians. State level baseline controls 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 A19: Joining Twitter and Followers

	Share of Donation Count from Followers				Share of Donation Amount from Followers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration	-0.020	-0.005	0.067***		0.124	0.404***	1.235***	
	[0.017]	[0.004]	[0.011]		[0.189]	[0.006]	[0.016]	
on Twitter	0.003	0.215***			-0.224	2.635***		
	[0.014]	[0.010]			[0.258]	[0.014]		
Log (campaign expenditure)	0.000	0.000	-0.001	0.000	0.001	0.001	-0.000	0.001
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Politician-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Week	Week	Week	Week	Week	Week	Week	Week
Week of the Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls x on Twitter		Yes	Yes	Yes		Yes	Yes	Yes
Observations	10,403	10,403	2,567	7,836	10,403	10,403	2,567	7,836
R-squared	0.801	0.801	0.807	0.797	0.719	0.720	0.694	0.727

Note: 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 proportion donations coming from followers (1)-(4) and the share of the amount of donations coming from followers in columns (5)-(8). This considers a sub-sample without 2009. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (8) and (8) only the experienced politicians. Baseline controls 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 A20: Joining Twitter and Donations (without 2009)

	Log (aggregate donations per week)				At least one donation per week			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	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

Note: 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 at least one donation in columns (5)-(8). This considers a sub-sample without 2009. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (8) and (8) only the experienced politicians. Baseline controls 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 A21: Joining Twitter Outside Campaign Periods

				Log (aggregate donations)		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All	New	Experienced	All	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

Note: 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) include all politicians while columns (2) and (4) include only the new and columns (3) and (6) only the experienced politicians. State level baseline controls 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 A22: Joining Twitter and Aggregate Donations: Politician and Week Fixed Effects

	Log (Aggregate donations)					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		All Politicians			New	Experienced
on Twitter x Twitter penetration	0.0861	0.303**	0.218**	0.389***	0.542***	-0.0551
	(0.133)	(0.144)	(0.107)	(0.121)	(0.164)	(0.141)
on Twitter	0.976***	0.147	0.133	-2.303	-5.373**	2.858
	(0.103)	(0.113)	(0.0897)	(1.406)	(2.065)	(2.244)
Twitter penetration	0.202	0.0106	0.0570	-0.0172	0.341	0.0402
	(0.150)	(0.522)	(0.350)	(0.354)	(0.378)	(0.399)
Log (campaign expenditure)			0.307***	0.306***	0.378***	0.169***
			(0.0166)	(0.0168)	(0.0187)	(0.0167)
Politician Fixed Effects		Yes	Yes	Yes	Yes	Yes
Week Fixed Effects		Yes	Yes	Yes	Yes	Yes
Baseline controls x on Twitter				Yes	Yes	Yes
Observations	30,354	30,354	30,341	30,341	17,907	12,434
R-squared	0.022	0.572	0.606	0.606	0.656	0.565

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 donations in a week. Columns (1) - (4) include all politicians while column (5) includes only new and column (6) only the experienced politicians. State level baseline controls 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 A23: Joining Twitter and Week of Month Fixed Effects

	Log (aggregate donations per week)				At least one donation per week			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration	0.350**	0.378**	0.692***	-0.217	0.047**	0.051**	0.084***	-0.014
	[0.152]	[0.149]	[0.173]	[0.245]	[0.020]	[0.020]	[0.024]	[0.034]
on Twitter	0.161	0.690	-3.194	7.474*	0.021	0.023	-0.477	0.877
	[0.110]	[2.524]	[2.871]	[4.492]	[0.015]	[0.349]	[0.408]	[0.581]
Log (campaign expenditure)	0.091***	0.091***	0.121***	0.079***	0.011***	0.011***	0.015***	0.009***
	[0.004]	[0.004]	[0.007]	[0.004]	[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
Week of the Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.823	0.823	0.885	0.787	0.788	0.788	0.847	0.752

Note: 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 at least one donation in columns (5)-(8). This considers a sub-sample without 2009. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (8) and (8) only the experienced politicians. Baseline controls 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 A24: Joining Twitter and and Time Trends

	Log (aggregate donations per week)				At least one donation per week			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	All	All	New	Experienced	All	All	New	Experienced
on Twitter x Twitter penetration	0.367	0.500*	0.850**	-0.116	0.049	0.066*	0.106**	-0.004
	[0.263]	[0.270]	[0.365]	[0.438]	[0.034]	[0.036]	[0.051]	[0.061]
on Twitter	15.942	105.211	130.204	97.174	1.540	13.055	17.615	9.880
	[180.825]	[187.974]	[244.212]	[321.624]	[23.703]	[25.129]	[33.467]	[43.526]
Log (campaign expenditure)	0.091***	0.091***	0.121***	0.079***	0.011***	0.011***	0.015***	0.009***
	[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
Linear and Quadratic Time Trend x on Twitter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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	0.823	0.823	0.885	0.787	0.788	0.788	0.847	0.752

Note: 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 at least one donation in columns (5)-(8). This considers a sub-sample without 2009. Columns (1)-(2) and (5)-(6) include all politicians while columns (3) and (7) include only new and columns (8) and (8) only the experienced politicians. Baseline controls 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.

Data Appendix

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.