informs
http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 67, No. 5, May 2021, pp. 2997–3021
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Social Media and Political Contributions: The Impact of New Technology on Political Competition

Maria Petrova,[a,b,c,d] **Ananya Sen,**[e] **Pinar Yildirim**[f]

[a] Pompeu Fabra University and Catalan Institution for Research and Advanced Studies (ICREA), 08002 Barcelona, Spain; [b] Barcelona Graduate School of Economics (GSE), 08002 Barcelona, Spain; [c] Institute for Political Economy and Governance (IPEG), 08002 Barcelona, Spain; [d] New Economic School, 121353 Moscow, Russia; [e] Carnegie Mellon University, Pittsburgh, Pennsylvania 15213; [f] Department of Marketing, The Wharton School, University of Pennsylvania, Philadelphia, Pennsylvania 19104

Contact: petrova.ma@gmail.com (MP); ananyase@andrew.cmu.edu, https://orcid.org/0000-0002-9082-6871 (AS); pyild@wharton.upenn.edu, https://orcid.org/0000-0002-6667-9365 (PY)

Received: March 28, 2017
Revised: October 15, 2018; September 19, 2019; March 26, 2020; April 11, 2020
Accepted: May 4, 2020
Published Online in Articles in Advance: September 29, 2020

https://doi.org/10.1287/mnsc.2020.3740

Abstract. Political campaigns are among the most sophisticated marketing exercises in the United States. As part of their marketing communication strategy, an increasing number of politicians adopt social media to inform their constituencies. This study documents the returns from adopting a new technology, namely Twitter, for politicians running for Congress by focusing on the change in campaign contributions received. We compare weekly donations received just before and just after a politician opens a Twitter account in regions with high and low levels of Twitter penetration, controlling for politician-month fixed effects. Specifically, over the course of a political campaign, we estimate that the differential effect of opening a Twitter account in regions with high versus low levels of Twitter penetration amounts to an increase of 0.7%–2% in donations for all politicians and 1%–3.1% for new politicians who were never elected to Congress before. In contrast, the effect of joining Twitter for experienced politicians remains negligibly small. We find some evidence consistent with the explanation that the effect is driven by new information about the candidates; for example, the effect is primarily driven by new donors rather than past donors, by candidates without Facebook accounts, and by tweeting more informatively. Overall, our findings imply that social media can intensify political competition by lowering the costs of disseminating information for new entrants to their constituents and thus may reduce the barriers to enter politics.

History: Accepted by Eric Anderson, marketing.
Funding: M. Petrova received financial support from the Spanish Ministry of Economy and Competitiveness [Grant ECO2014-55555-P] and the Ministry of Education and Science of the Russian Federation [Grant 14.U04.31.0002]. A. Sen received financial support from the Jean Jacques Laffont Digital Chair. P. Yildirim received financial support from the Wharton Dean's Research Fund and the Mack Institute.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/mnsc.2020.3740.

Keywords: social media • competition • technology adoption • political donations • political marketing

1. Introduction

Political campaigns are among the most expensive and sophisticated marketing efforts in the United States. In the 2018 electoral cycle, campaign spending by House and Senate candidates reached a total of more than $1 billion for each of the two houses.[1] To inform and persuade voters, candidates rely on a variety of communication strategies, including advertising, print and broadcast media, and speeches along the campaign trail. Moreover, over the past few years we have observed politicians adopting new communication technologies such as social media. So far, the literature has produced mixed evidence that adopting social media as a communication technology helps brands and consumers (e.g., Hoffman and Fodor 2010, Naylor et al. 2012, Kumar et al. 2013, Laroche et al. 2013, Gans et al. 2016, Gong et al. 2017). In a similar vein, it is not clear if this adoption is useful for politicians and alters any aspects of political competition. This question is particularly timely as we head into the 2020 presidential election because of increased interest in social media's influence on electoral races.

We study the effect of new communication technology on campaign contributions. More specifically, we focus on politicians' adoption of Twitter and its effect on political donations received while they are running for the U.S. Congress. Throughout the analysis, we focus on how Twitter adoption may lead to differential benefits for new politicians relative to more experienced politicians. Documenting such heterogeneity in benefits from adopting social media is particularly important because there is well-documented evidence that incumbents in the United States hold significant financial and informational advantages over newcomers (Ansolabehere and Snyder 2000, Prat 2002, Prior 2006). We ask whether adopting social media can mitigate this incumbency advantage by giving new politicians access to an alternate, relatively cost-effective technology to communicate with their constituencies about their candidacy and raise awareness.

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 he or she raised. To study how adopting Twitter influences the amount of political donations received more rigorously, we use a difference-in-differences approach. We combine data on 1,834 politicians who opened a personal Twitter account between 2009 and 2014, campaign contributions received, expenditures incurred by the candidates, and Twitter's penetration in the politician's region, which we use as a proxy for users' exposure to information disseminated from Twitter relative to other information. We ask whether joining Twitter had a differential effect on donations in high- and low-Twitter-penetration states. We control for the politician-month fixed effects to account for politician-specific unobserved time-varying factors, such as being more progressive, being more tech savvy, or being at a different stage of campaigning. Our identifying assumption is that unobserved determinants of donations did not differentially affect donations in high- versus low-Twitter-penetration states. Said differently, the differences between contribution flows, unexplained by politician-month fixed effects, would remain the same in regions with different levels of Twitter penetration in the absence of politicians' entry to Twitter, also known as the *parallel-trend assumption*.[2]

We find that right after a candidate started to post on Twitter, his or her weekly aggregate donations went up, more so in states where Twitter penetration is high. We focus on donations below $1,000 because smaller donors are more likely to respond to information disseminated via social media. We find that the differential increase in donations between high- and low-Twitter-penetration states ranges from 2.9% in 2009 to 22.8% in 2014. However, this gain is significantly positive only for new politicians who have never been elected to Congress before, that is, not for the experienced candidates. The persuasion rate associated with donations after opening a Twitter channel is approximately 1% (DellaVigna and Gentzkow 2010). This rate is lower than the average media persuasion rates reported in the literature but is comparable to the rates reported for direct mailing (Gerber and Green 2000) and political advertising (Spenkuch and Toniatti 2016). Overall, our results are consistent with new technology being helpful to promote competition, specifically among politicians.

To strengthen our identification claims, we use a series of placebo tests. Our identifying assumption is that joining Twitter is not related to within-politician-month unobserved determinants of donations in high- versus low-Twitter-penetration states. This assumption could be violated when some other fund-raising or marketing activity is happening at the same time, even though, a priori, there are no particular reasons to think that these activities should affect donations differentially depending on the level of Twitter penetration. To cope with this possibility, we investigate how politicians' key marketing activities change around the time of adopting Twitter. First, using Federal Election Commission's (FEC) data on campaign spending, we study whether there are any contemporaneous increases in 12 different expense categories, including general advertising, fund-raising events, campaign materials, and travel. We find that there is no discontinuous increase in various types of campaign spending around the time of Twitter entry across high- and low-Twitter-penetration areas, even though political contributions are strongly correlated with campaign spending in a given week. Second, we find that media and blog coverage of the politicians do not change significantly around the time of Twitter entry. Third, we find that there is no increase in advertising spending on television around the time of Twitter entry, even though political ads seem to be a significant driver of political donations (see, e.g., Urban and Niebler 2014). Finally, we test whether Twitter penetration is just a proxy for other characteristics, such as income, education, political preferences, internet access, party affiliation, and racial composition, which may influence donations in the same way, and we find that it is unlikely to be the case. Overall, the results in all our placebo specifications are consistent with our identifying assumptions; that is, unobserved heterogeneity is unlikely to explain our results. To alleviate concerns that there could be some residual bias coming from unobservables, in the Online Appendix A, we conduct Altonji–Elder–Taber tests (Altonji et al. 2005). We show that in our particular setting, to attribute our entire difference-in-differences estimates to selection effects, selection on unobservables would have to be more than 10.4 times greater than the selection on observables.

To explain the mechanism through which donations increase, we borrow from the literature on advertising (Nelson 1974). Adopting a new communication technology, similar to advertising, helps politicians to gain support through an information and/or persuasion channel. The information mechanism suggests that voters who were not previously familiar with a candidate become informed about the candidate and his or her policy proposals. The persuasion mechanism suggests that voters who are already informed about the candidates and their policy stances would be further persuaded or mobilized to provide support. We provide some evidence consistent with the information mechanism in our setting. First, we find that entry to Twitter increases political donations from donors who did not support the politicians before but not from repeat donors. Second, we find that the effect is driven by the politicians who did not have a Facebook account before, in contrast to politicians who joined Facebook before Twitter. Third, the analysis of tweet content and frequency suggests that more frequent and more informative tweets (e.g., including links to websites, responding to news fast, or more antiestablishment tweets) are associated with receiving higher contributions after adopting Twitter. Fourth, we find that the donations to a candidate come predominantly from same-state donors as opposed to donors from other states. Finally, political candidates for the House of Representatives in high-Twitter-penetration regions see a quantitatively higher jump in donations after adopting Twitter compared with Senate candidates whose name recognition is arguably higher. Overall, these findings are consistent with new information driving political contributions by increasing potential donors' awareness of the politicians and their proposed policies.

A broader implication of our study is that the adoption of Twitter can reduce the gap in fund-raising opportunities between new and experienced politicians, which, in turn, can lower barriers to entry to national politics and increase political competition. Furthermore, we find qualitatively similar results when we analyze the impact of Facebook adoption on political donations within a similar empirical framework. Thus, new technologies indeed have a potential to change the incentives of prospective entrants and, ultimately, make American politics more competitive. Because social media provides access to a relatively cheap advertising platform, our results have more general implications for platforms such as Twitter and Facebook allowing new brands and products to enter some markets and inform consumers, making those markets more competitive.

Our paper contributes to several areas in the literature. First, we contribute to studies of the impact of media and information and communication technologies (ICTs) on competition (Fudenberg et al. 1983, Fudenberg and Tirole 1985, Aghion et al. 2005), consumer demand and financial gain (Fang and Peress 2009, Engelberg and Parsons 2011, Goh et al. 2011, Bollinger et al. 2013), voting behavior (DellaVigna and Kaplan 2007; Chiang and Knight 2011; Enikolopov et al. 2011; Gentzkow et al. 2011, 2014; Rotesi 2019), social outcomes (Jensen and Oster 2009, La Ferrara et al. 2012, Enikolopov et al. 2020), and policy decisions (Strömberg 2004, Eisensee and Strömberg 2007, Snyder and Strömberg 2010). We complement this literature by highlighting a mechanism through which media could influence political competition. We demonstrate how the advent of a new communication technology, social media in general and Twitter in particular, can alter political competition by improving opportunities for new candidates to raise funds and inform voters in a cost-effective fashion.

Second, our paper is also related to a stream of studies in marketing, management, and economics that discuss the outcomes and returns from adoption of social media (e.g., Hoffman and Fodor 2010, Kumar et al. 2013, Culotta and Cutler 2016). Gong et al. (2017) and Seiler et al. (2017) study the impact of advertising of television content in Chinese microblogs on subsequent television series viewership. Enikolopov et al. (2020) study the impact of social media on corporate accountability. Gans et al. (2016) and Ma et al. (2015) focus on social media as a tool for consumers to exhibit voice and for firms to respond to consumer complaints. Acemoglu et al. (2017) and Enikolopov et al. (2020) analyze the effects of social media content and penetration on subsequent protest participation. Qin et al. (2017) study the content and impact of social media in China for collective-action outcomes, whereas Qin (2013) looks at the relationship between Chinese microblog penetration and drug quality. In contrast with these studies, we focus our investigation on the strategic benefit of entry into an online social network for public personalities, specifically for politicians, by quantifying their financial gain and investigating the mechanisms behind it in detail.

Finally, we also contribute to the studies of political campaigns and political communication in marketing. Marketing scholars have long been interested in the determinants and design of political races (Rosenthal and Sen 1969, 1973, 1977), with the interest resurfacing more recently (Gordon et al. 2012). Soberman and Sadoulet (2007) studied how campaign limits influence political spending and found that tighter limits stimulate more aggressive advertising from competing parties. Gordon and Hartmann (2013, 2016) estimate the effectiveness of advertising on political races and also focus on how the structure of political competition in the United States shapes advertising spending. Xiang and Sarvary (2007), Gal-Or et al. (2012), Yildirim et al. (2013), and Zhu and Dukes (2015) focus on how media outlets strategically adopt political biases to maximize their revenue. This paper contributes to these earlier studies by demonstrating the effect of communication on social media on politicians' fund-raising ability and electoral competition.

The rest of the paper is organized as follows. Section 2 provides a review of the literature and institutional details on the use of social media by politicians, and Section 3 provides a summary of the data we use. Section 4 provides the framework for the empirical analysis, Section 5 details the results, and Section 6 discusses the mechanism. Finally, Section 7 concludes.

2. Background

2.1. Use of Social Media by Politicians

Until recently, traditional media held the role of being the primary information channel for politicians, so obtaining coverage in newspapers and television outlets has been crucial for electoral success. Candidates further disseminate information about their candidacy and policy goals through speeches they give along the campaign trail and through public appearances (Garcia-Jimeno and Yildirim 2015). Today, a reported 80% of heads of states around the world use Twitter to communicate with their constituencies.[3] Compared with campaign messages, the content of this communication is more personal and includes information about politicians' lives and activities outside politics. Although 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. In 2018, Barack Obama had more than 100 million Twitter followers, Senator Orin Hatch had more than 100,000, and Representative Paul Cook had more than 14,000. In our data, the total number of candidates who had been using Twitter increased from 741 in 2009 to 1,024 in 2010, to 1,488 in 2012, and to 1,834 in 2014.

After the 2008 presidential election, scholars predicted increased and targeted web use by political campaigns at the federal and local levels (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 because of its confinement to 140 characters (which was extended to 280 characters in November 2017) and its lack of restrictions on viewing messages from those with whom one is not directly connected. 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 media (Towner and Dulio 2012, Campante et al. 2018).

The primary benefits of the SNS as a campaign tool include low cost, ability to recruit volunteers and receive contributions, and its accessibility to all candidates, whether well known or lesser known (Gueorguieva 2008). In addition to these benefits, Twitter brings new possibilities for candidate–voter interaction because the "@username" function allows candidates to reply directly to other users and promote a dialogue, allowing candidates to bypass traditional media outlets (Lassen and Brown 2010).

Given these benefits and the ubiquity of Twitter in campaigns, scholars and pundits have begun studying whether the overall use of social media by politicians actually matters for political outcomes (Baumgartner and Morris 2010, Kushin and Yamamoto 2010, Zhang et al. 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, whereas Hong and Nadler (2011) demonstrate how the use of Twitter correlates with shifts in polling outcomes 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). As the number of Twitter users continues to increase, so does the fraction of them who report using the site to gather political information (Smith and Rainie 2008, Smith 2011). According to a University of Oxford and Reuters joint report, in 2017, 56% of the surveyed individuals in the United States followed at least one politician on Twitter (Kalogeropoulos 2017). For politicians, policymakers, and consumers of social media, documenting the causal impact of Twitter with mechanisms at play is essential.

2.2. Media and Incumbency Advantage

Incumbency advantage is among the best-documented electoral patterns in the United States (Ansolabehere et al. 2006a). Incumbents reportedly enjoyed increasing numbers of electoral wins, starting with a 1%–2% point advantage in the 1940s and rising to an 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), 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.

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 reelection 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. By documenting how social media can benefit new candidates relative to experienced ones, we complement the literature that 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). Although we recognize that there may be downsides to more competitive political races, we posit that more information about candidates and their policy positions stands to benefit voters.

Traditional media can influence voter decisions through their coverage and candidate endorsements. Voters also favor candidates 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. 2006a) than their opponents. Ansolabehere et al. (2006b) 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 because of his or her public recognition and because of his or her 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 are correlated with lower responsibility and accountability toward constituents by politicians (Carson et al. 2007). These concerns together suggest that new technologies that can reduce the incumbency advantage can result in elections becoming more competitive. Although there are benefits to more competitive elections, they may also bring along less desirable outcomes such as more polarized and negative tones in campaigns and excessive spending for political marketing. Complementing these earlier studies, our study finds that new rather than experienced politicians have an advantage in opening an account on social media, promising to mitigate the incumbency advantage.

3. Data

Our study uses data from a variety of sources, each of which we discuss in this section.

3.1. List of Politicians

First, using the FEC database, we compiled a list of all politicians 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 the election cycles of 2010, 2012, and 2014.[4] We refined this list based on the Twitter accounts detailed later.

3.2. Contributions to Politicians

The data source for the political donations is the 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 political action committees or other organizations. In most of our analysis, we limit our attention to donations of less than $1,000[6] because 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 his or her location. We provide detailed summary statistics for the donations and politician characteristics in Tables A8 and A9 in the Online Appendix A. In our analysis, we aggregate donations at the politician-week level.

3.3. Campaign Expenditures

The source of our data for campaign expenses of a politician is the FEC. The FEC database on disbursements lists the exact amount, date, purpose, and payee for each expenditure item by each candidate. Note that, by law, for any politician to accept donations, he or she needs to be registered by the FEC and has to report all of expenses with the above-mentioned details if the payment exceeds $200. Note that recorded expenditures can be negative because of refunds given back to contributors.

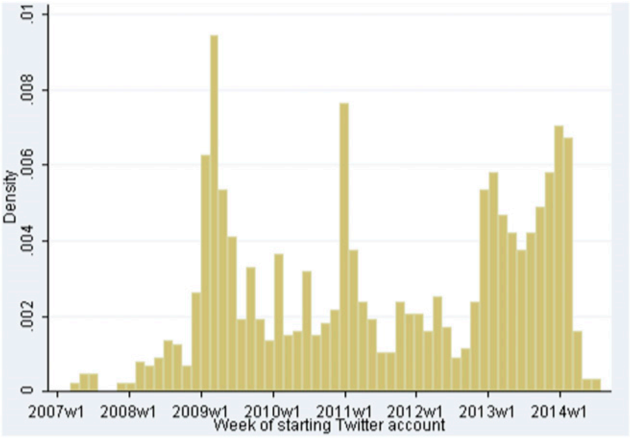
In addition, we record the purpose of each expense labeled based on the 12 categories specified by the FEC: administrative, travel, solicitation and fund-raising, advertising, polling, campaign materials, campaign events, transfers, loan repayments, refunds, contributions, and donations to charitable or civic organizations. Detailed descriptions of each category can be found in Online Appendix B, Section B.3.

3.4. Twitter Account Data

For each politician in our initial list from the FEC, we searched for his or her Twitter handle.[7] We combine an automated script with a manual check to gather information about whether a politician has a Twitter account or not and collect data from the account. We identify the date that the account was first activated and supplement it with data on the number of tweets and retweets, the text of the tweets, and the number of followers.

Figure 1 shows the Twitter account opening dates for politicians in our initial list between 2007 and 2014. The distribution indicates that politicians opened accounts on Twitter continuously between 2009 and 2014 and that there was little entry prior to 2009. Variation in entry dates reduces the concern that politicians' entry time may be strategic, coinciding with the timing of specific events such as election years. Moreover, the

Figure 1. (Color online) Dates (Week) of Opening an Account on Twitter



majority of politicians adopt Twitter in a nonelection year, again indicating that the account opening date is not always strategic.

The increase in the donations received by a politician may partially be an artifact of the calls for donations and donation links posted on Twitter. If this is the case, Twitter adoption would increase donations not only because of increased information about politicians but also because these links act as reminders to donate. Moreover, campaign accounts are typically temporary because they are opened strategically before an election and closed after the election. To reduce these concerns, we remove these accounts dedicated to campaigns in our benchmark analysis. 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.[8]

3.5. Twitter Penetration

We need a measure of Twitter penetration, which would essentially capture the probability with which an average person would see a Twitter message from a political candidate. This probability depends on both the extensive margin (how many people are on Twitter) and the intensive margin (how much time each person spends on Twitter) because it is easier to notice content from a candidate for somebody who uses Twitter more often. One problem is that neither the total number of Twitter users by geography nor the average intensity of using Twitter is observable because Twitter does not share these types of data with researchers. Some scholars use geotagged tweets to infer penetration by geography, but given that only 2% of all tweets are geotagged, this approach is likely to lead to skewed estimates (Kinder-Kurlanda et al. 2017).[9]

Our approach to overcome this problem is to use comScore's representative panel of internet users. Our preferred measure is based on counting the number of visits to Twitter and to all other sites by comScore respondents. To create this measure, we aggregate the total number of Twitter visits by comScore respondents in a state and divide it by the total number of all site visits by comScore respondents in that state, thus obtaining our proxy for a probability that an average internet user in a state would get exposed to some content on Twitter.[10] More formally, we calculate the average pageviews for each state s and year y as

$$\text{Twitter Penetration}_{sy} = \left(\frac{\text{Number of pageviews on Twitter}_{sy}}{\text{All pageviews}_{sy}}\right).$$

Figure 2 shows the Twitter penetration measure by state and year. We use 11 other measures of Twitter penetration, 9 of which use the comScore panel (total number of comScore households on Twitter, total comScore duration spent on Twitter, average and median weekly share of time spent on Twitter, average and median weekly share of sessions on Twitter, median share of Twitter pageviews, and average and median weekly proportion of households visiting Twitter) and two measures (proportion of households using Twitter in the last 7 days, proportion of households using Twitter in the last 30 days) using Simmons Oneview, an alternative panel to comScore's. In Online Appendix A, Section A.6, we show that our results are robust to using any of those alternative measures. We also run a population-weighted regression with our baseline penetration measure to find similar results. Details on these measures and summary statistics are provided in Online Appendix A, Section A.6, and the benchmark specifications with these alternate measures are provided in Tables A14 and A15 in Online Appendix A.

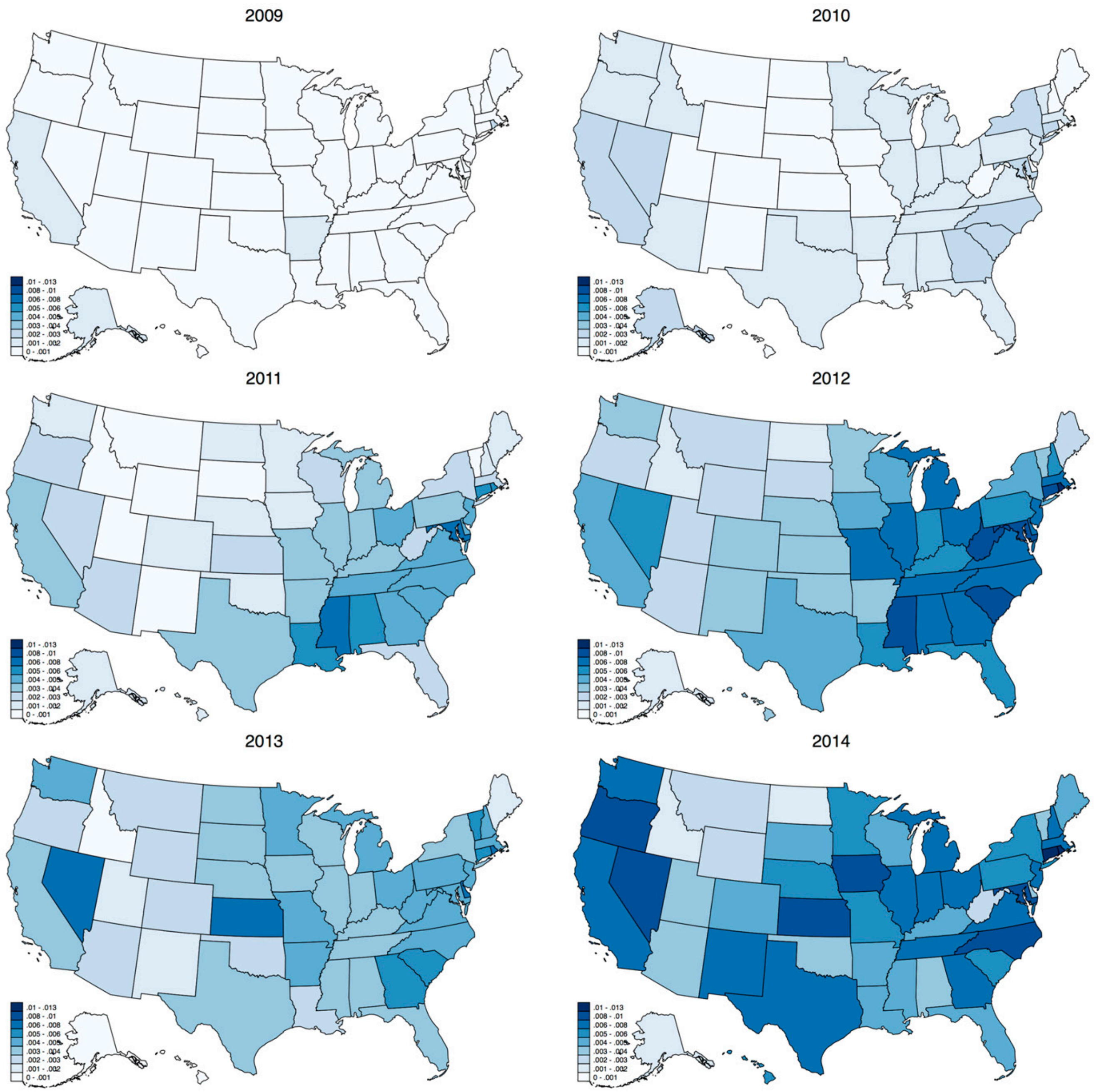
3.6. Advertising Spending Data

We collect additional advertising spending data from Kantar Media's Adspender database, dating back to as early as 2009. This data set covers the dollar value of broadcast television advertising for each week. Note that the advertising spending values here may differ from advertising campaign expenses for two reasons: first, because the FEC expenses may cover other formats of advertising and, second, because Adspender reports the spending for the ads broadcast in that week, whereas campaign expenses may reflect a purchase for a future date.

3.7. News and Blogging Data

For each politician in our list, we collect information on the number of media mentions for a window of 10 weeks

Figure 2. (Color online) Twitter Penetration Over the Years, in Absolute Numbers



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 Blogger. We use this information to check whether there are systematically more media mentions of a politician around the time he or she starts a Twitter account. If there are other events related to a politician's campaign around the time of opening a Twitter account that affect donations, media may also cover them, resulting in a higher number of mentions. Using media mentions, we can also test for the presence of other contemporaneous events.

3.8. Politicians' Personal Data

We collect data on the personal characteristics of the politicians using two different data sources. The first source is the FEC, and the second is the VoteSmart database, which provides information about politicians' age, education, and voting history. More than 50% of the data are missing on votesmart.org, and when possible, we support the missing information through manual data collection.

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 he or she had never been elected to Congress before. If the politician already won an election in the past, then he or she is classified as an experienced politician. We present summary statistics separately for the experienced and new politicians in Table A9 in online Appendix A. Throughout this paper, we check for heterogeneous effects of Twitter adoption by classifying the politicians as new versus experienced.[11]

3.9. Facebook Adoption

We also collect data on politicians' adoption of the most prominent competing social network, Facebook. We collected the dates of the first public post on Facebook for all the politicians in our list and use those as the dates of adopting Facebook. Less than 1% of politicians open an account in the same week on Twitter and Facebook. We 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).

3.10. State Demographic and Voting Characteristics

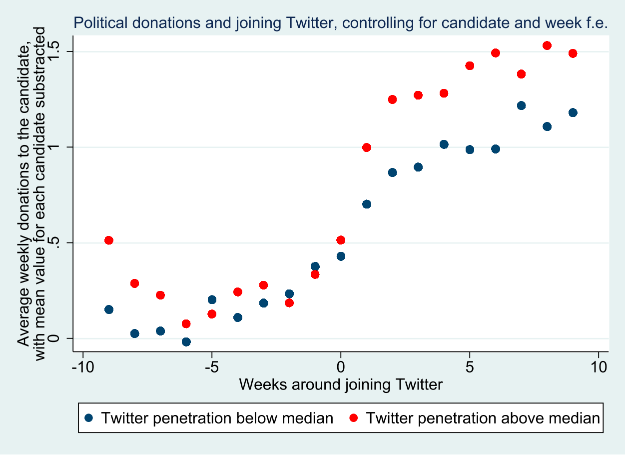
In our analyses, we control for state characteristics including demographics such as household income and population obtained from the Census. In extensions of the analysis, we also consider correlations with the share of rich (i.e., share of households with incomes of more than $250,000), share with a college education, and share of the African-American population using data from the Census. We use the data on the Republican vote share (received by George W. Bush in the 2004 presidential election) obtained from uselectionatlas.org.

4. Empirical Framework

4.1. Identification

Our key empirical hypothesis is that politicians who adopt Twitter see gains in campaign contributions. In Section A.3 of online Appendix A, we formally model how politicians gain from adopting Twitter.[12] Figure 3 shows how political donations evolve in high- and low-Twitter-penetration states, controlling only for politician and week fixed effects, before and after Twitter entry.[13] There are two takeaways from this figure. First, donations indeed seem to increase after joining Twitter, but not before, and furthermore, this effect is stronger in places with high Twitter penetration. Second, there seem to be no significant differences 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 3 illustrates our main point: entry to Twitter seems to help politicians to increase their political donations, and the support is higher in high-Twitter-penetration places.

Figure 3. (Color online) Donations and Twitter Penetration



Technically, we aim to estimate the following equation:

$$Outcome_{it} = \beta_0 + \beta_1 OnTwitter_{it} + \beta_2 OnTwitter_{it} \times Penetration_{sy} + \gamma_{pm} + X_{it} + \varepsilon_{it}, \quad (1)$$

where $Penetration_{sy}$ is Twitter penetration in state s in year y, γ_{pm} is a politician-month fixed effect, and X_{it} is a vector of controls.[14] To identify β_2, we need an assumption that the error term is not *differentially* correlated with unobserved factors. For example, even if some unobserved campaign activity is present and is changing sharply at the time of the Twitter entry, it should not be a problem for our estimation as long as this activity does not differentially affect political donations in high- and low-Twitter-penetration states. Formally, the following assumption should hold:

Assumption 1. $\text{corr}(OnTwitter_{it} \times Penetration_{sy}, \varepsilon_{it} | OnTwitter_{it}, X_{it}, \gamma_{pm}) = 0$.

Under this assumption, we can correctly estimate the differential impact of joining Twitter in high- versus low-Twitter-penetration states, even though the estimate of the direct effect of Twitter β_1 or of the full effect of Twitter $\beta_1 + \beta_2 \times Penetration_{sy}$ could be biased. It is, in fact, a parallel-trend assumption applied to our specific empirical framework.[15]

In more detail, the expected bias of the ordinary least squares estimate in Equation (1) is

$$E\begin{pmatrix}\hat{\beta_0}\\ \hat{\beta_1}\\ \hat{\beta_2}\\ \dots\end{pmatrix} = \begin{pmatrix}\beta_0\\ \beta_1\\ \beta_2\\ \dots\end{pmatrix} + (X'X)^{-1}\begin{pmatrix} E(\varepsilon_{it}|X_{it},\gamma_{pm})\\ \text{cov}(OnTwitter_{it},\varepsilon_{it}|X_{it},\gamma_{pm})\\ \text{cov}(OnTwitter_{it}\times Penetration_{st}, \\ \varepsilon_{it}|X_{it},\gamma_{pm})\\ \dots\end{pmatrix}.$$

Assumption 1 is needed to consistently identify β_2 without bias in the expectation. At the same time, to identify both β_1 and β_2, we need a stronger assumption[16] that the error term needs to be uncorrelated with unobserved determinants of decisions to join Twitter, conditional on fixed effects and other observables.[17]

Note that although we have regions with varying levels of Twitter penetration, we do not have a proper control market where Twitter penetration is exactly zero. Here we implicitly make the assumption that using the interaction term, we can linearly extrapolate to markets with no penetration. This assumption is not far from reality because the Twitter penetration scores are indeed very close to zero in some markets (e.g., Wyoming or Montana). Under this assumption, the *OnTwitter* dummy captures any activity that happens when politicians join Twitter but that is uncorrelated with penetration (see the discussion in endnote 16).[18]

Note also that in principle the decision to join Twitter $OnTwitter_{it}$ could be a function of a (slowly changing) Twitter penetration rate without violation of Assumptions 1 and 2 as long as the Twitter penetration rate $Penetration_{sy}$ available in our data at the state-year level is perfectly collinear with politician-month fixed effects.

In what follows, we are going to use the most conservative approach to estimate Equation (1); thus we rely on Assumption 1. Using this assumption, we focus on estimating the differential impact of joining Twitter in high- versus low-Twitter-penetration states. We will talk more about the value of Twitter for politicians in Section 5.3.

4.2. Identification Checks

Because the specification in Equation (1) controls flexibly for time-invariant and time-variant characteristics of the politicians and their states, the main threat to identification is contemporaneous unobserved marketing activity of these politicians, which, deliberately or by chance, could lead to the jump in donations in the same week when these politicians joined Twitter and more so in the states with higher Twitter penetration.

We unfortunately cannot directly test the identifying assumption and check whether joining Twitter coincides with some unobservable factor. Instead, we conduct two exercises with the aim of strengthening our identification argument. First, we check whether the observable potential drivers of donations are systematically related to joining Twitter, differentially in high- versus low-Twitter-penetration states, by providing placebo or "balance" tests (see Pei et al. 2019). Second, in Online Appendix A, Section A.2, we consider the potential bias resulting from unobservables, that is, whether they are positively correlated with observables, using the Altonji–Elder–Taber framework (Altonji et al. 2005). We estimate how large the selection on unobservables has to be to explain our findings.

We report the results of placebo tests that test whether joining Twitter indeed coincides with some other measures of activity in Section 5.4. These tests check whether there is a differential activity of higher news and blog coverage, higher spending on television advertising, or other types of campaign activities when politicians adopt Twitter in high- and low-Twitter-penetration regions. Figures 4–6 illustrate how the news coverage, blog mentions, and advertising spending change around the week of Twitter adoption in high- and low-Twitter-penetration regions. The figures do not show significant changes in these activities before or after Twitter entry for different penetration regions, and this finding is consistent with our identifying assumptions.

Figure 4. (Color online) Number of News Mentions and Twitter Penetration

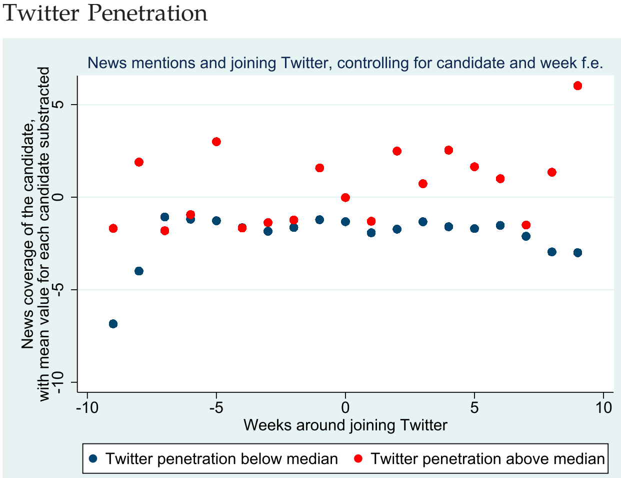


Figure 5. (Color online) Number of Blog Mentions and Twitter Penetration

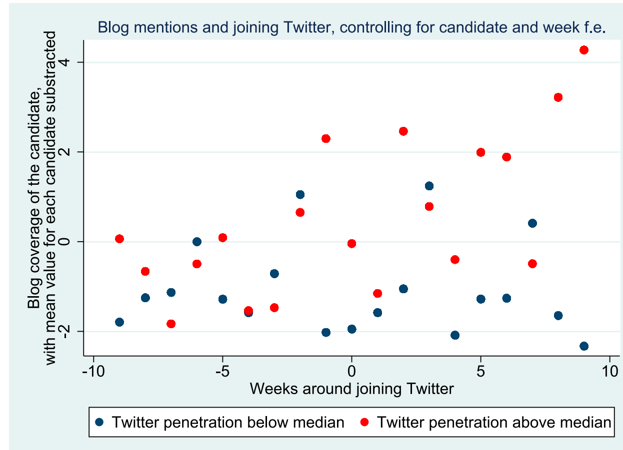
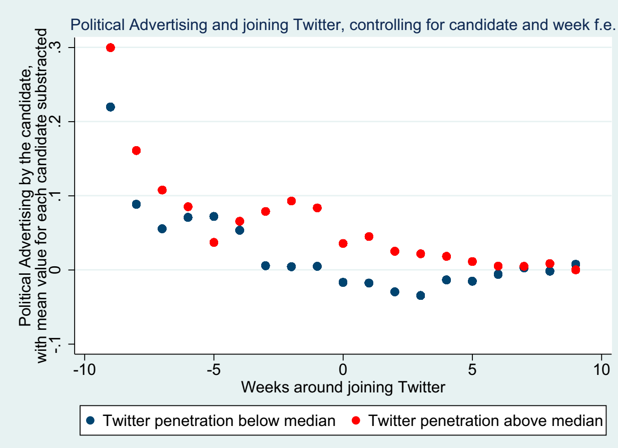


Figure 6. (Color online) Political Advertising and Twitter Penetration



5. Empirical Results

5.1. Baseline Results

We present the results from the specification given in Equation (1) for aggregate donations in Table 1, for donating at least once in Table 2, and for the number of donations in Table 3. Table 1 demonstrates a positive and significant impact of the interaction of Twitter and Twitter penetration on aggregate political donations for all politicians. In the tables, we also report the implied effect of joining Twitter by comparing the gains in higher-Twitter-penetration states relative to the lower-Twitter-penetration states, where *high* and *low* are defined as the 75th and 25th percentiles in state penetration level, respectively. This difference is given in the last two rows of all the tables and separately for the beginning (2009) and end years (2014) in our data. We do not report the aggregate effects of Twitter at any particular level of Twitter penetration (e.g., mean or median) because under Assumption 1 we cannot guarantee that those numbers are estimated consistently.[19]

The results in these tables imply that for a simple specification without additional controls, the differential impact of joining Twitter ranges from a 2.9% weekly increase in 2009 to a 22.8% weekly increase in 2014 (Table 1, column (1)). These numbers describe the average increase in donations during the month of joining Twitter, and we discuss potential ways to aggregate effects over the course of the campaign in Section 5.3. Even-numbered columns in Tables 1–3 report the results conditional on two additional controls: joining Twitter interacted with population and median household income. We add these controls because the impact of joining Twitter could be higher in larger markets, where potential donors are richer, and we do not want our coefficient of interest to pick up those relationships. Nevertheless, one can see that in all three tables and specifications, adding these controls does not change the coefficient of interest largely and increases it rather than decreasing it, which is consistent with no unobserved heterogeneity explaining away our results (Altonji et al. 2005). The corresponding results with controls for these interactions are indeed slightly more precise in most cases.[20] The direct coefficient for joining Twitter is mostly insignificant, consistent with the prediction that joining Twitter should not affect markets with very small penetration.[21]

Table 1. Twitter Adoption and log(*Aggregate Donations*)

	log(*Aggregate Donations*)					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	All	All	New	New	Experienced	Experienced
OnTwitter × *Twit_Penet*	102.6499**	106.1455**	186.0268***	192.2501***	−45.0641	−47.0084
	(45.5244)	(45.5292)	(44.9294)	(45.7696)	(93.7545)	(91.0756)
OnTwitter	0.1879	1.3162	0.1268	2.3393	0.3961*	−0.0791
	(0.1126)	(1.0235)	(0.1140)	(1.5472)	(0.2248)	(2.0678)
Observations	565,968	565,968	236,740	236,740	329,228	329,228
R^2	0.8215	0.8215	0.8828	0.8828	0.7856	0.7856
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.029**	0.03**	0.047***	0.048***	−0.013	−0.013
Implied Twitter effect for 2014	0.228**	0.236**	0.414***	0.428***	−0.1	−0.105

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is log(*Aggregate Donations*). Columns (1) and (2) include all politicians, whereas columns (3) and (4) include only new politicians and columns (5) and (6) have experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 2. Twitter Adoption and Probability of Receiving at Least One Donation

	Probability of one donation					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	All	All	New	New	Experienced	Experienced
OnTwitter × *Twit_Penet*	13.7776**	14.3168**	22.5307***	23.4135***	−1.9080	−2.0584
	(5.8924)	(5.9123)	(6.3244)	(6.4678)	(12.0430)	(11.7725)
OnTwitter	0.0243	0.1972	0.0218	0.3403	0.0407	0.0035
	(0.0149)	(0.1503)	(0.0168)	(0.2057)	(0.0301)	(0.2909)
Observations	565,968	565,968	236,740	236,740	329,228	329,228
R^2	0.7865	0.7865	0.8448	0.8449	0.7508	0.7508
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.004**	0.004**	0.006***	0.006***	−0.001	−0.001
Implied Twitter effect for 2014	0.031**	0.032**	0.05***	0.052***	−0.004	−0.005

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is probability of receiving at least one donation. Columns (1) and (2) include all politicians, whereas columns (3) and (4) include only new politicians and columns (5) and (6) have experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Tables 1–3 also report an important dimension of heterogeneity of the results because joining Twitter seems to help new politicians, who were never elected before (columns (3) and (4) in all three tables), without much of an effect for experienced politicians, who had been elected at least once before deciding to open a Twitter account. More specifically, for new politicians, the differential impact of joining Twitter on weekly donations during the first month after entry ranges from 4.7% in 2009 to 41.4% in 2014 (Table 1, column (3)). In contrast, the interaction coefficient for experienced politicians is negative, though not statistically significant (Table 1, columns (5) and (6)), with the absolute value of the coefficient being at least

Table 3. Twitter Adoption and log(*Number of Donations*)

	log(*Number of Donations*)					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	All	All	New	New	Experienced	Experienced
OnTwitter × *Twit_Penet*	16.9626	17.4442	41.2259***	42.5467***	−25.3309	−26.4579
	(12.3434)	(12.3865)	(11.5946)	(11.5548)	(24.0077)	(23.0095)
OnTwitter	0.0533	0.2116	0.0226	0.4715	0.1328**	−0.1396
	(0.0323)	(0.1734)	(0.0294)	(0.3578)	(0.0567)	(0.4622)
Observations	565,968	565,968	236,740	236,740	329,228	329,228
R^2	0.8384	0.8384	0.9007	0.9007	0.8006	0.8007
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.005	0.005	0.01***	0.011***	−0.007	−0.007
Implied Twitter effect for 2014	0.038	0.039	0.092***	0.095***	−0.056	−0.059

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is log(*Number of Donations*). Columns (1) and (2) include all politicians, whereas columns (3) and (4) include only new politicians and columns (5) and (6) have experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

four times smaller than that for new politicians.[22] Overall, these results are consistent with the finding that social media are helpful for candidates who are lesser known but not for more experienced politicians. The results of the estimation for the probability of receiving at least one donation (Table 2) and for the number of donations (Table 3) are largely consistent with the results for the aggregate donations, with the effects for new politicians again being the largest and most precisely estimated. In Section 5.3, we derive the implications of these coefficients in a detailed manner, taking the observed decline of the Twitter effect over time.

5.2. Baseline Results with Varying Window Specifications

The results we discussed so far do not allow us to interpret the magnitudes beyond the month when politicians open their Twitter accounts. Politician-month fixed effects in Equation (1) absorb any effect after the new month starts. Interpreting the magnitudes given in Tables 1–3 for the months in a campaign following the month of opening a Twitter account thus requires making strong assumptions. One way to deal with this problem is to use less restrictive fixed effects such as politician fixed effects. The primary purpose of this section is to provide some alternative estimates to understand the magnitudes.

In this section, we offer an alternate method to estimate the differential impact of Twitter using politician fixed effects in a way that is qualitatively similar to the results in Figure 3. Specifically, we report what happens before and after a politician opens a Twitter account for windows of 5–10 and 20 weeks after opening and 8 weeks before the opening. We estimate the following window specification:

$$Outcome_{it} = \beta_0 + \beta_1 OnTwitter_{it} + \beta_2 OnTwitter_{it} \times Penetration_{sy} + \delta_i + X_{it} + \varepsilon_{it}$$

for the $t_0 - 8 < t < t_0 + k$ time window, where δ_i is a politician fixed effect.[23]

These results, presented in Table 4, show that the coefficients for joining Twitter interacted with Twitter penetration are consistent with our main results. The impact of Twitter on aggregate political donations is particularly strong for new politicians but much smaller in magnitude and not statistically significant for the experienced ones. The magnitudes in columns (1) and (2) imply that the differential impact of Twitter is 2.4% in 2009 and 20.9% in 2014 for the sample of all politicians (Table 4, column (1)) and from 3.5% to 28.7% for new politicians (Table 4, column (2)) for the same years.[24] These magnitudes are slightly smaller than the ones in Table 1. To the extent that we trust both estimates, we can use the comparison of coefficients in Tables 1 and 4 to understand the decline of the Twitter effect over the course of the campaign.

5.3. Discussion of Magnitudes

The results from Table 1 imply that the differential impact of Twitter on weekly donations ranges from a 2.9% increase in 2009 to a 22.8% increase in 2014 when using a specification with politician-month fixed effects, all based on donations of less than $1,000. In this section, we discuss what magnitudes these numbers could imply, referring to the differential Twitter effect

Table 4. Baseline Results: Eight-Week Window with Politician Fixed Effects

	log(*Aggregated Donations*)			Probability of one donation			log(*Number of Donations*)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	All	New	Old	All	New	Old	All	New	Old
OnTwitter × *Twit_Penet*	93.9519**	126.7358**	−13.2064	12.5811**	15.0845**	−0.6215	16.3467	25.8044**	−5.4879
	(38.9716)	(50.8035)	(44.1856)	(5.0375)	(6.8434)	(5.8806)	(10.8844)	(12.3834)	(12.0133)
OnTwitter	0.0303	0.1225	0.0862	0.0071	0.0212	0.0133	0.0056	0.0304	0.0081
	(0.1119)	(0.1288)	(0.1679)	(0.0148)	(0.0183)	(0.0232)	(0.0326)	(0.0319)	(0.0454)
Observations	24,094	14,160	9,929	24,094	14,160	9,929	24,094	14,160	9,929
R^2	0.5869	0.6077	0.5720	0.5460	0.5667	0.5237	0.6016	0.6354	0.6005
Politician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.024**	0.035**	−0.003	0.003**	0.004**	0	0.004	0.007**	−0.001
Implied Twitter effect for 2014	0.209**	0.287**	−0.027	0.028**	0.034**	−0.001	0.036	0.058**	−0.011

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variables are log(*Number of Donations*), probability of receiving donations, and log(*Number of Donations*). Columns (1), (4), and (7) include all politicians, whereas columns (2), (5), and (8) include only new politicians and columns (3), (6), and (9) have experienced politicians. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician and week fixed effects.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 5. Amount of Donations: Different Windows with Politician Fixed Effects

	All politicians: log(*Aggregate Donations*)						
	5 weeks	6 weeks	7 weeks	8 weeks	9 weeks	10 weeks	20 weeks
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OnTwitter × *Twit_Penet*	100.1897**	89.1422**	92.7713**	93.9519**	85.6743**	80.6435**	50.1190
	(40.6520)	(41.4398)	(39.0579)	(38.9716)	(36.8228)	(37.8201)	(37.0327)
OnTwitter	0.0081	0.0323	0.0348	0.0303	0.0705	0.1042	0.5155***
	(0.1219)	(0.1194)	(0.1153)	(0.1119)	(0.1064)	(0.1105)	(0.1107)
Observations	19,221	20,846	22,470	24,094	25,716	27,336	43,508
R^2	0.6018	0.5932	0.5894	0.5869	0.5832	0.5807	0.5635
Politician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.025**	0.022**	0.023**	0.024**	0.021**	0.02**	0.013
Implied Twitter effect for 2014	0.223**	0.198**	0.206**	0.209**	0.191**	0.179**	0.111

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is log(*Aggregate Donations*). Columns (1)–(7) include all politicians. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician and week fixed effects.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

in high- versus low-Twitter-penetration states (75th versus 25th percentile). Note that under Assumption 1, we are only able to consistently estimate the differential effect of *OnTwitter* in contrast to the full aggregate effect of joining Twitter at some particular level of Twitter penetration.[25]

Note that the average weekly donation amount in the months the politicians join Twitter is \$1,534 (Table A8 in Online Appendix A). On average, politicians join Twitter in the second week of the month and are active for 2.79 weeks. Based on Table 1, the average differential effect of Twitter ranges from $\$1,534 \times 0.029 = \$44$ per week in 2009 to $\$1,534 \times 0.228 = \$350$ per week in 2014, amounting to a gain of $\$44 \times 2.79 = \$124$ for the month of opening an account in 2009 and $350 \times 2.79 = \$976$ for 2014.

A lower bound of the estimated impact of Twitter can be calculated by assuming that the effect of Twitter disappears at the end of a short period. The results in Table 4 provide us with the opportunity to understand how the implied effect of Twitter changes across the eight weeks after opening the account. The implied Twitter effect for 2009 and 2014 from column (1) of Table 4 indicates a gain of $\$1,534 \times 0.024 \times 8 = \$294$ in 2009 and $\$1,534 \times 0.209 \times 8 = \$2,565$ in 2014. These numbers are the lower bound of the Twitter effect under the assumption of zero effect after eight weeks. The latter number suggests that the implied effect of Twitter corresponds to at least 0.7% of all donations received by an average House candidate over the course of the campaign and 1.7% of all donations of \$1,000 and less.[26] These numbers

Table 6. Amount of Donations: Different Windows with Politician Fixed Effects

	New politicians: log(*Aggregate Donations*)						
	5 weeks	6 weeks	7 weeks	8 weeks	9 weeks	10 weeks	20 weeks
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OnTwitter × *Twit_Penet*	124.1443**	115.2081**	121.8793**	126.7358**	124.9643**	122.2513**	133.0385**
	(49.4201)	(50.2453)	(49.4881)	(50.8035)	(51.3200)	(50.8119)	(52.2574)
OnTwitter	0.0976	0.1113	0.1293	0.1225	0.1720	0.2266	0.7307***
	(0.1287)	(0.1262)	(0.1254)	(0.1288)	(0.1323)	(0.1393)	(0.1559)
Observations	11,328	12,274	13,218	14,160	15,098	16,034	25,257
R^2	0.6162	0.6106	0.6080	0.6077	0.6053	0.6048	0.5890
Politician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.035**	0.032**	0.034**	0.035**	0.035**	0.034**	0.037**
Implied Twitter effect for 2014	0.281**	0.26**	0.276**	0.287**	0.283**	0.276**	0.301**

Notes. Robust standard errors clustered at the level of the state and week in parenthesis. The dependent variable is log(*Aggregate Donations*). Columns (1)–(7) include new politicians. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician and week fixed effects.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 7. Amount of Donations: Different Windows with Politician Fixed Effects

	Experienced Politicians: log(*Aggregate Donations*)						
	5 weeks	6 weeks	7 weeks	8 weeks	9 weeks	10 weeks	20 weeks
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OnTwitter × *Twit_Penet*	17.0589	−2.7135	−4.7562	−13.2064	−29.6278	−30.0255	−26.3213
	(42.0674)	(46.2546)	(43.7108)	(44.1856)	(40.4304)	(40.4767)	(42.1172)
OnTwitter	0.0278	0.0856	0.0720	0.0862	0.1305	0.1337	0.2238
	(0.1796)	(0.1884)	(0.1793)	(0.1679)	(0.1618)	(0.1674)	(0.1528)
Observations	7,886	8,567	9,247	9,929	10,610	11,296	18,244
R^2	0.5907	0.5792	0.5756	0.5720	0.5674	0.5637	0.5468
Politician fixed effects	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y
Implied Twitter effect for 2009	0.004	−0.001	−0.001	−0.003	−0.007	−0.007	−0.006
Implied Twitter effect for 2014	0.034	−0.005	−0.01	−0.027	−0.059	−0.06	−0.043

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is log(*Aggregate Donations*). Columns (1)–(7) include experienced politicians. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician and week fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

constitute, on average, 1% of all donations to new House candidates and 2.7% of all donations of less than \$1,000 over the course of the campaign.[27]

Note that these eight weeks consist of, on average, 2.79 weeks from the first month, on which our fixed-effects estimation is based, and the remaining 5.21 weeks. Thus, from these numbers, we can deduce that the average differential weekly increases associated with Twitter after the first month of data are (\$294 − \$124)/5.21 = \$33 per week for 2009 and (\$2,565 − \$976)/5.21 = \$304 per week for 2014. The weekly magnitudes become smaller after the first month of donations.

An upper bound of the effect can be calculated assuming that the effect of Twitter remains at the same level until the end of the campaign period as it did in the second month. On average, politicians open Twitter accounts about 25 weeks before the elections. For this period, the implied gain translates to \$124 (the effect during the first month) + \$33 × (25 − 2.79) = \$857 (the effect during the remaining campaign period) in 2009 and \$976 + \$304 × (25 − 2.79) = \$7,728 in 2014. Based on the latter number, the upper bound on the implied effect of Twitter is 2% for all donations received by an average House candidate over the course of the campaign and 5.4% for all donations of less than \$1,000. Similarly, for a new politician, the calculated upper bound corresponds to 3.1% of all campaign donations to new House candidates and 8.2% of all donations of less than \$1,000.

As an additional exercise to put our estimates in perspective, we compute persuasion rates (DellaVigna and Kaplan 2007, DellaVigna and Gentzkow 2010; see Section A.1 in Online Appendix A). The main takeaway from this exercise is that the persuasion rates implied by our estimates are remarkably similar to those in political advertising (Spenkuch and Toniatti 2016).

5.4. Placebo Tests

Our identifying assumption is that conditional on politician-month fixed effects and other controls, entry on Twitter across states of high and low Twitter penetration is not related to unobserved heterogeneity in donations. In other words, we assume that within a given month for a particular politician, the exact timing of joining Twitter is as good as random across areas of high and low Twitter penetration. This assumption is violated if some other fund-raising or marketing activity coincides in time with Twitter adoption differentially across areas with different levels of Twitter penetration. Although we cannot test this assumption directly, we conduct a number of tests to ensure that at least the observable potential determinants of donations cannot explain away our results. In this section, following the theoretical arguments by Pei et al. (2019), we carry out *placebo* or *balance* tests to analyze, based on observables, whether there are any obvious violations of our identifying assumption. Pei et al. (2019) argue that a balance-test approach, which puts the observables on the left-hand side as the dependent variable, is a helpful exercise similar to those used in randomized trials comparing baseline or pretreatment characteristics.[28]

5.4.1. Campaign Expenditures. A potential threat to our casual claim is the possibility of a correlation between the timing of Twitter entry and other unobserved marketing activities. Although unobserved marketing activities are, by definition, the activities for which we do not have data, the campaign expenditures of politicians can be a reasonable proxy for them. When and how campaign funds are spent are reported to the FEC in detail (see Section 3 and Online Appendix B), and the FEC classifies campaign disbursements into 12 categories. The categories most relevant to marketing activities include advertising expenses, campaign material expenses, fund-raising expenses, and travel expenses (which may include town visits on the campaign trail). We estimate a placebo specification using the weekly expenditure in each category (as well as the total expenditure) as the dependent variable. One concern with the expenditure data is how noisy they are; however, we find that the weekly total campaign expenditure is highly correlated with the aggregate campaign contributions received in the same week, as demonstrated in Table A17 of Online Appendix A, for each expense category. This reduces the concern that the expenditure data contain high levels of noise.

Table 8 provides the placebos with campaign expenditures in different categories. If there are other unobserved marketing activities that coincide with opening a Twitter account and these activities vary across the high- and low-Twitter-penetration regions, then such activities may pose an alternate explanation to the effect we attribute to Twitter. Reducing this concern, we find that the coefficient of entry on Twitter interacted with Twitter penetration is statistically insignificant for all listed expense categories as well as the total expenses. The differential effects of Twitter across high- and low-Twitter-penetration areas are small in magnitude and never statistically significant. We also report the baseline results with inclusion of contemporaneous and lagged campaign expenditures in Table A18 of Online Appendix A. To the extent that campaign expenditures capture other activities of the politicians the same week they open a Twitter account, these findings are consistent with the causal interpretation of results in Tables 1–3.

5.4.2. Political Advertising. We next test for the potential simultaneous increase in advertising activity by the candidates using a second data set from Kantar Media's AdSpender database. We check whether there was a differential increase in political ad spending around the time a candidate joined Twitter for high- versus low-Twitter-penetration states. Columns (1)–(3) of Table 9 present these results. The results are consistent with joining Twitter not being associated with an increase in political ad spending after controlling for politician-month fixed effects. The interaction term and the direct effect are insignificant for all and new politicians. For experienced politicians (column (3)), the interaction term is negative, though statistically insignificant. Thus, in all samples, joining Twitter is not associated with an increase in political advertising spending, and therefore, a spurious relationship between opening a Twitter account and political advertising cannot explain our results.

Note that we do not observe digital advertising, which may include social media advertising, email marketing, search advertising, or display advertising, and our advertising spending placebo does not address these activities. We do not, however, see a significant increase in the disaggregated campaign expenditures (which include categories such as advertising and campaign materials) in the week a politician joins Twitter. If the campaigns allocated extra funds for digital marketing at this time, because payments for digital ads are typically billed within days, these efforts would likely be captured in the weekly campaign expenses.

5.4.3. News and Blogs Coverage. Next, we test whether the timing of adopting Twitter may coincide with other external events reported in the media, possibly as part of a larger public relations campaign. Media mentions of a politician capture both additional information shocks voters receive and the events in which a politician is involved, which may drive donations independently of Twitter. To address this concern, we collect data on the mentions of a politician in traditional and social media. We run a search for each politician's name in Google News and Google Blogger for a 10-week window around the time of opening a Twitter account.[29]

Columns (4)–(6) of Table 9 report a placebo test that uses the logged weekly news reports of a politician as the dependent variable. Overall, the estimates suggest that opening a Twitter account is not correlated with the differential number of news articles about a politician in the overall sample (column (4)) or with new (column (5)) and experienced (column (6)) politicians across areas with high and low Twitter penetration.

Columns (7)–(9) of Table 9 report a placebo specification with the logged number of blog mentions. The effect of adopting Twitter is not significantly correlated with the number of blog posts for the overall sample. For new politicians (columns (8)), the interaction term is negative rather than positive and marginally significant. This negative sign may suggest, for instance, a displacement of politician-related blog content from the more traditional blogging platforms to Twitter after a politician himself or herself joins Twitter. Nevertheless, because the relationship is negative, the coverage on other blogs cannot explain away the effect of Twitter adoption.[30] Note that Google Blogger data used do not include Twitter and Facebook.[31]

Table 8. Campaign Expenditure Placebo Analysis

Panel A: Campaign expenditure placebo I

Variable	(1) log(*Total Expenditure*)	(2) log(*Contributions*)	(3) log(*Polling Expenses*)	(4) log(*Refund to Donors*)	(5) log(*Fundraising*)	(6) log(*Transfers to Committees*)	(7) log(*Travel Expenses*)
OnTwitter × *Twit_Penet*	24.5295	−12.5698	−0.6529	1.0771	2.6789	−2.8861	−5.9670
	(43.9563)	(9.9327)	(8.7970)	(1.0577)	(13.9863)	(2.8872)	(15.4036)
OnTwitter	−0.0002	−0.2113	−0.0234	0.0226	0.6984	0.0214	−0.2215
	(1.5214)	(0.2611)	(0.2009)	(0.0221)	(0.6493)	(0.0278)	(0.4379)
Observations	561,339	561,598	561,600	561,594	561,576	561,600	561,548
R^2	0.8710	0.3316	0.3251	0.2718	0.6456	0.2717	0.5939
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.007	−0.003	0	0	0.001	−0.001	−0.002
Implied Twitter effect for 2014	0.055	−0.028	−0.001	0.002	0.006	−0.006	−0.013

Panel B: Campaign expenditure placebo II

	(8) log(*Administrative Expenses*)	(9) log(*Advertising Expenditure*)	(10) log(*Events*)	(11) log(*Materials*)	(12) log(*Donations*)	(13) log(*Loan Repayments*)
OnTwitter × *Twit_Penet*	13.4955	17.5680	5.4400	8.1173	−2.1121	0.3731
	(22.9729)	(15.9738)	(12.5658)	(13.2697)	(3.3032)	(0.9381)
OnTwitter	−0.8601	−0.1807	0.5236	0.1613	0.1971	−0.0880
	(0.6406)	(0.4189)	(0.3131)	(0.3412)	(0.1686)	(0.0715)
Observations	561,538	561,579	561,590	561,591	561,595	561,600
R^2	0.8369	0.6210	0.5227	0.4963	0.3928	0.2637
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.004	0.005	0.002	0.002	−0.001	0
Implied Twitter effect for 2014	0.03	0.039	0.012	0.018	−0.005	0.001

Notes. Robust standard errors clustered at the level of the state and week in parentheses. Columns (1)–(13) include all politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

6. Mechanisms

Our main findings suggest that a politician's adoption of Twitter causes an increase in the aggregate donations he or she receives. We consider two potential mechanisms driving donations: information and persuasion. Adoption and activity on Twitter may help a politician to increase awareness about his or her candidacy and policies, which, in turn, can increase his or her support from the electorate. Intuitively, we expect the gains to be higher for new politicians compared with experienced politicians because 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

Table 9. Political Ads, News and Blogs Placebo Analysis

	log(*Political Advertising Expenditure*)			log(*Number of News Mentions*)			log(*Number of Blog Mentions*)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	All	New	Experienced	All	New	Experienced	All	New	Experienced
OnTwitter × *Twit_Penet*	−13.9824	11.1326	−58.8757	0.4565	−2.4421	5.9242	−5.7416	−7.2800*	−2.9491
	(18.0394)	(14.4600)	(52.2719)	(3.9450)	(3.3989)	(9.0824)	(4.1593)	(3.6545)	(8.2101)
OnTwitter	0.3212	−0.0515	0.7542*	0.0341	−0.0358	0.1325	−0.0359	−0.0177	−0.0533
	(0.1937)	(0.1642)	(0.4118)	(0.1092)	(0.0727)	(0.2323)	(0.1115)	(0.1038)	(0.2043)
Observations	565,968	236,740	329,228	46,379	28,320	18,059	46,379	28,320	18,059
R^2	0.8136	0.8301	0.8020	0.9207	0.9275	0.9106	0.8584	0.8588	0.8488
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yess	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	−0.004	0.003	−0.016	0	−0.001	0.001	−0.001	−0.002*	−0.001
Implied Twitter effect for 2014	−0.031	0.025	−0.131	0.001	−0.006	0.01	−0.013	−0.016*	−0.005

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable are log(*Political Advertising Expenditure*), log(*Number of News Mentions*), and log(*Number of Blog Mentions*), respectively. Columns (1), (4), and (7) include all politicians, whereas columns (2), (5), and (8) include only new politicians and columns (3), (6), and (9) have the experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

encouraging them to donate more. Through either mechanism, the donations raised by a politician can be expected to increase after Twitter adoption. If information is the main channel, however, we expect the effect to be more pronounced for new politicians and for donations from first-time donors. Similarly, gains from being on Twitter are expected to be higher for the in-state compared with the out-of-state donations and for House versus the Senate candidates.

Our baseline findings demonstrate that social media raise donations only for new politicians and not for experienced ones. Our theoretical framework (given in Online Appendix A) and our main results are consistent with the information mechanism proposed earlier. With this information mechanism, the marginal return to information provision through Twitter is likely lower for experienced candidates because their quality, experience, and policy positions are better known. For a political newcomer, there is more new information to share.

In this section, we present a number of additional tests that allow us to provide some evidence in line with the mechanisms with which our data are consistent. First, we check whether our estimates are stronger for new versus 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. Second, we test whether the effect is driven by the politicians who did not have a Facebook account before or by politicians who joined Facebook before Twitter and are thus more experienced with social media. Third, we check whether the candidates for the Senate, who run in state-level elections and have better name recognition, gain more than the candidates for the House, who are elected from smaller districts. Finally, we also analyze tweeting activity by politicians to document how differences in tweeting activity and the content of tweets affect donations.

6.1. New vs. Repeat Donors

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 actual donor population. Second, in line with the information channel, it is plausible that Twitter helps politicians to expand their donor base, with some new donors hearing about and contributing to the campaign for the first time. In this section, we investigate whether new and repeat donors respond differentially to the opening of a Twitter account, estimating Equation (1) separately for these groups of donors.

These results in Table 10 show that opening a Twitter account increases the amount and the number of donations received by politicians, more so in high-Twitter-penetration states. This effect is especially pronounced for new politicians and is negative but not significant for experienced politicians. Numerically, the magnitude of the effect is a 2.8% increase in 2009 and a 22.2% increase in 2014 for all politicians when considering aggregate donations from new donors (column (1)). For new politicians, the implied effect for donations from new donors is 5% and 44.8% for the same years (column (2)). In contrast, for donations

Table 10. Amount of Donations and New vs. Repeat Donors

	New donors			Repeat donors		
Variable	(1) All	(2) New	(3) Experienced	(4) All	(5) New	(6) Experienced
			Panel A: log(*Aggregate Donations*)			
OnTwitter × *Twit_Penet*	99.6026**	201.2764***	−82.2807	−23.4208	13.5236	−80.3688
	(39.5139)	(42.8484)	(74.3038)	(37.0208)	(19.4423)	(84.5136)
OnTwitter	0.6378	2.2815	−1.5874	−0.2534	−0.5769	0.2076
	(0.7134)	(1.5024)	(1.5364)	(0.8247)	(0.8508)	(1.5842)
Observations	565,968	236,740	329,228	565,968	236,740	329,228
R^2	0.7850	0.8725	0.7332	0.7626	0.8080	0.7359
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yess	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.028**	0.05***	−0.023	−0.007	0.003	−0.022
Implied Twitter effect for 2014	0.222**	0.448***	−0.183	−0.052	0.03	−0.179
			Panel B: log(*Number of Donations*)			
OnTwitter × *Twit_Penet*	19.0058*	43.1319***	−24.0642	−6.4079	3.1616	−20.8431
	(10.0928)	(11.0250)	(16.4680)	(8.3034)	(4.4554)	(18.5322)
OnTwitter	0.2554*	0.4975	−0.0834	−0.1068	−0.0713	−0.1357
	(0.1360)	(0.3617)	(0.4017)	(0.1962)	(0.1299)	(0.3680)
Observations	565,968	236,740	329,228	565,968	236,740	329,228
R^2	0.8169	0.8892	0.7642	0.7891	0.8484	0.7615
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	0.005*	0.011***	−0.007	−0.002	0.001	−0.006
Implied Twitter effect for 2014	0.042*	0.096***	−0.054	−0.014	0.007	−0.046

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variables are log(*Aggregate Donations*) and log(*Number of Donations*). Columns (1) and (4) include all politicians, whereas columns (2) and (5) include only new politicians and columns (3) and (6) have the experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects. A statistical test comparing the weekly aggregate donations from new versus repeat donors shows the following p-values: 0.000 (all politicians), 0.000 (new politicians), and 0.971 (experienced politicians). We do not see a significant difference in the number of donations.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

from repeat donors, we do not see any significant increase, and the corresponding coefficients for the full sample (column (4) in panels A and B) are small and negative.[32]

6.2. Politicians with Facebook Accounts Prior to Joining Twitter

The information mechanism implies that the impact of Twitter might be smaller for politicians who already use some other social media, such as Facebook. In this section, we test whether our results are substantially different for politicians who joined Facebook before Twitter compared with those for whom their Twitter account is their first social media account.[33] These results are summarized in Table 11. As one can see, there was no significant impact of opening a Twitter account for those who had a Facebook account before. The coefficients are negative but not statistically significant.[34] In contrast, in Table A12 in Online Appendix A, we show that excluding politicians who had a Facebook account before leads to results that are qualitatively similar to the baseline.

6.3. House and Senate Candidates

In this section, we compare the gains for the candidates running for the Senate and the House. The name recognition of candidates running for the Senate is generally higher than that of candidates running for the House because all states are represented by only two senators but often by a larger number of representatives. Moreover, senators are appointed for a six-year term versus a two-year term for House members. Thus, we expect the average candidate for the House to obtain higher gains from communicating via Twitter than the average candidate for the Senate.

Table 11. Politicians with and Without Facebook Before

	log(*Aggregate Donations*)				Probability of donation			
	No FB before	No FB before	Had FB before	Had FB before	No FB before	No FB before	Had FB before	Had FB before
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All	All	All	All	All	All	All	All
OnTwitter × *Twit_Penet*	107.1144***	110.6932***	−208.8425	−112.7912	14.4419***	14.9910***	−40.1547	−32.9786
	(36.5950)	(36.5206)	(270.5396)	(443.9461)	(4.8938)	(4.9012)	(37.2622)	(56.4349)
OnTwitter	0.1537*	1.2504	1.4660	6.8097	0.0182	0.1862	0.2243*	1.3319*
	(0.0859)	(0.9892)	(1.0423)	(5.5263)	(0.0123)	(0.1447)	(0.1289)	(0.7843)
Observations	550,239	550,239	15,689	15,689	550,239	550,239	15,689	15,689
R^2	0.8240	0.8240	0.7674	0.7674	0.7885	0.7885	0.7129	0.7129
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.03***	0.031***	−0.061	−0.033	0.004***	0.004***	−0.012	−0.01
Implied Twitter effect for 2014	0.238***	0.246***	−0.388	−0.209	0.032***	0.033***	−0.075	−0.061

Notes. Robust standard errors clustered at the level of the state. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week fixed effects. We cluster only at the state level because in the restricted sample we do not have enough clusters to compute standard errors. We control for week fixed effects instead of week-of-month fixed effects to ensure computation of standard errors. FB, Facebook.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Focusing on the sign and magnitude of the interaction effect, we find the results, reported in Table 12, to be in line with this prediction. More specifically, the interaction effect of Twitter is positive and significant for the full sample and new House candidates for aggregate donations (columns (4) and (5) of panel A) and for the number of donations (column (5) of panel B) in Table 12. The effect for the average House candidate ranges from 3% in 2009 to 24.8% in 2014. For experienced politicians who are members of the House, we see a negative but statistically insignificant result, consistent with our previous findings. In contrast, all the estimates for Senate candidates (columns (1)–(3) of panels A and B)[35] are small in magnitude and are far from being statistically significant.[36]

6.4. Tweeting Activity and Tweet Content

In this section, we study whether the gain of new politicians is correlated with their tweeting activity and specific content. To this end, we focus on the coefficient of the triple interaction term between joining Twitter,[37] Twitter penetration, and (various measures of) tweeting activity. We consider a 25-week window around politicians' adoption of Twitter.

The results from the analysis of tweeting activity are given in Tables A21 and A22 of Online Appendix A. In sum, we find that donations go up for politicians who post more original tweets rather than retweets, ptuse more hyperlinks, use more antiestablishment-related words, or appear to be more "plugged in." We use a psychological approach to text analysis using 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 those words. The scale that we use was developed by Pennebaker et al. (2015) and is intended to measure personal characteristics of an individual. We find no differential impact for politicians with various psychological traits, but we find some marginal increase for politicians who are plugged in, that is, those who have a social style related to staying informed about recent news and developments. However, these results should be interpreted with caution because they use all subsequent Twitter posting behavior of a politician to assess the impact of joining Twitter during the first weeks after opening an account.

6.5. Within-State 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 office in that state. To validate use of the within-state Twitter penetration measure, we compare whether donors within a state and from out of state respond differently to a politician's Twitter entry.

Table 12. Joining Twitter and Amount of Donations: House vs. Senate Candidates

	Senate			House		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	All	New	Experienced	All	New	Experienced
	Panel A: log(*Aggregate Donations*)					
OnTwitter × *Twit_Penet*	34.7339	48.6398	43.2330	119.0656**	214.1968***	−57.8678
	(73.9788)	(106.8262)	(107.1972)	(50.7529)	(48.7895)	(106.4910)
OnTwitter	−3.1263	−1.3372	−4.6257	2.4824*	2.7287	1.7364
	(2.0686)	(2.5507)	(4.1722)	(1.3541)	(1.8950)	(2.2820)
Observations	114,816	50,408	64,408	451,152	186,332	264,820
R^2	0.8665	0.9249	0.8259	0.8077	0.8643	0.7748
Politician-month fixed effects	Y	Y	Y	Y	Y	Y
Week-of-month fixed effects	Y	Y	Y	Y	Y	Y
Baseline controls × *OnTwitter*	Y	Y	Y	Y	Y	Y
Implied Twitter effect for 2009	0.01	0.014	0.016	0.03**	0.054***	−0.014
Implied Twitter effect for 2014	0.09	0.126	0.114	0.248**	0.484***	−0.083
	Panel B: log(*Number of Donations*)					
OnTwitter × *Twit_Penet*	−6.5753	−16.0041	5.7861	22.3269	51.2158***	−30.8124
	(20.5819)	(20.4530)	(35.6365)	(13.7621)	(12.0619)	(25.7055)
OnTwitter	−0.6366	−0.7959	−0.3724	0.3957	0.6293	−0.0380
	(0.6569)	(0.7602)	(1.1739)	(0.2404)	(0.4758)	(0.4227)
Observations	114,816	50,408	64,408	451,152	186,332	264,820
R^2	0.8935	0.9339	0.8607	0.8131	0.8773	0.7785
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	Yes	Yes	Yes	Yes	Yes	Yes
Implied Twitter effect for 2009	−0.002	−0.005	0.002	0.006	0.013***	−0.008
Implied Twitter effect for 2014	−0.017	−0.041	0.015	0.047	0.116***	−0.044

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variables are log(*Aggregate Donations*) and log(*Number of Donations*). Columns (1) and (4) include all politicians, whereas columns (2) and (5) include only new politicians and columns (3) and (6) have the experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects. Adding a triple interaction term to compare the aggregate weekly donations to the House versus Senate candidates finds the following p-values: 0.249 (all politicians), 0.020 (new politicians), and 0.423 (experienced politicians). For the number of donations comparison, the corresponding p-values are 0.162 (all), 0.001 (new), and 0.304 (experienced).

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

The results in Table 13 demonstrate that this intuition is supported by the data. The table shows that the within-state estimates are statistically significant and positive across all politicians (columns (1)–(2)), with the strongest effect for those who are new (column (3)–(4)). Quantitatively, the magnitudes are comparable but smaller than the baseline results. The estimates are again insignificant for experienced politicians (column (5)–(6)). For out-of-state donors in Table 13, we find that the Twitter entry interacted with Twitter penetration is statistically insignificant for the overall sample and only marginally significant for new politicians, with significantly smaller coefficients in magnitude for out-of-state versus in-state donations.

Overall, the results in Tables 10–13 are consistent with information rather than persuasion mechanisms, implying that Twitter helps politicians to make their candidacy and policy positions more visible, especially for new politicians who were never elected before. In addition, Tables A21 and A22 in Online Appendix A 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. Conclusion

Electoral campaigns, from data collection and voter targeting to advertising and political communications, are among the most sophisticated and costly marketing efforts. A notable change in these efforts during the past decade is the intensified use of social media platforms to reach out to and inform voters, partially

Table 13. Joining Twitter and Within the State Donations

	log(*Aggregate Donations*)					
Variable	(1) All	(2) All	(3) New	(4) New	(5) Experienced	(6) Experienced
	Within state					
OnTwitter × *Twit_Penet*	99.5491**	100.9357**	164.8527***	167.4275***	−14.4344	−16.8130
	(43.4447)	(43.5136)	(38.3601)	(38.8466)	(97.8290)	(95.5988)
OnTwitter	0.1757	0.5550	0.1347	1.2038	0.3262	−0.3620
	(0.1171)	(1.0078)	(0.1037)	(1.4707)	(0.2351)	(1.8667)
Observations	543,504	543,504	225,904	225,904	317,600	317,600
R^2	0.7961	0.7961	0.8640	0.8640	0.7573	0.7573
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week of month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.025**	0.025**	0.041***	0.042***	−0.004	−0.005
Implied Twitter effect for 2014	0.221**	0.225**	0.373***	0.379***	−0.032	−0.037
	Outside state					
OnTwitter × *Twit_Penet*	19.9318	22.6562	87.8919*	93.0614*	−98.7879*	−101.0485*
	(42.1108)	(41.7695)	(46.1417)	(46.6828)	(58.7697)	(55.5853)
OnTwitter	0.1158	0.9958	0.0628	1.9295**	0.3106**	−0.2368
	(0.1001)	(0.6411)	(0.0990)	(0.9470)	(0.1541)	(1.3118)
Observations	565,888	565,888	236,712	236,712	329,176	329,176
R^2	0.7203	0.7203	0.8036	0.8036	0.6792	0.6792
Politician-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Week of month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls × *OnTwitter*	No	Yes	No	Yes	No	Yes
Implied Twitter effect for 2009	0.006	0.006	0.022*	0.023*	−0.027*	−0.028*
Implied Twitter effect for 2014	0.044	0.05	0.196*	0.207*	−0.22*	−0.225*

Notes. Robust standard errors clustered at the level of the state and week in parentheses. The dependent variable is log(*Aggregate Donations*). Columns (1) and (2) include all politicians, whereas columns (3) and (4) include only new politicians and columns (5) and (6) have the experienced politicians. State-level baseline controls interacted with the politician being on Twitter include the median household income and population size. The average of pageviews relative to all pageviews in state-year is used as the Twitter penetration measure. All specifications include politician-month and week-of-month fixed effects.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

eliminating dependence on traditional media outlets such as newspapers and television. The essential question is whether the adoption of social media technology alters any aspects of political competition or electoral politics. More broadly, can innovations in information technologies change the way markets operate? In this study, we document that entry on social media (Twitter, Facebook) can help to increase funds and attract new donors for new politicians. Overall, our results imply that social media can intensify electoral competition by reducing the barriers for entrants to raise money.

Many avenues of future research lie at the intersection of adoption of new communication technologies and marketing. Future studies may expand the findings from our study to investigate whether the same trends follow for brands, specifically if the availability of new communication technologies such as Twitter can help new brands to ward off competition from incumbents. Similarly, studying the extent of substitution between new and traditional media channels is at the core of marketing and advertising, and scholars may be interested in documenting whether traditional and social media are complements or substitutes in delivering brand and product information to consumers. If they are, readers may gain from learning how these new technologies alter the way consumers perceive products or form their consideration sets.

Acknowledgments

The authors thank Yann Algan, Pablo Barbera, Daniel Chen, Sylvain Ferret, Jacques Cremer, Stefano DellaVigna, Ruben Enikolopov, Yosh Halberstam, Pooyan Khashabi, Brian Knight, Ting Li, Jennifer Pan, Paul Seabright, Jas Sekhon, James Snyder, David Strömberg, Alessandro Tarozzi, Joel Waldfogel, Christophe Van den Bulte, Karine Van der Straeten, Yanhao Wei, and seminar participants at Toulouse School of Economics, Universitat Pompeu Fabra, Stanford Digital Marketing Conference, 19th International Society for New Institutional Economics Conference (Harvard), Social Media and Political Participation Conference (New York University Florence), 9th IP, Software and Internet Conference (Toulouse), Economics of Network Industries Workshop (Paris), Zentrum für Europäische Wirtschaftsforschung

Information and Communication Technologies conference (Mannheim), Munich Summer Institute, Media Economics Workshop (Zurich), University of Virginia Marketing Seminar, and Conference on Digital Experimentation (Massachusetts Institute of Technology). for helpful comments. The authors are also grateful to Yosh Halberstam and Brian Knight for kindly sharing the data on followers for 2012 candidates and to Andrei Simonov for kindly sharing his data on political advertising. The authors also are grateful to Jack Beckwith, Renata Gaineddenova, Erqi Ge, Fernando Fernandez, Maria Ptashkina, and Shawn Zamechek for excellent research assistance. Author names are listed in alphabetical order.

Endnotes

[1] Center for Responsive Politics, https://www.opensecrets.org/overview/index.php?display=T&type=A&cycle=2018 (accessed on September 8, 2016).

[2] Because all states had nonzero Twitter penetration in our sample, we assume that the results from nonzero-Twitter-penetration states can be linearly extrapolated to calculate the counterfactual for a state with no Twitter usage.

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

[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.

[6] We also study and report the results for donations between \$1,000 and \$3,000 and more than \$3,000 in Section A.5 of Online Appendix A.

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

[8] The results including the campaign accounts can be found in Table A11 in Online Appendix A. Inclusion of these accounts does not seem to change our qualitative results.

[9] Note that the decision to put geotagging on a tweet is not random and can be endogenous to local characteristics.

[10] Note that our measure is highly correlated with the share of Twitter users among comScore respondents in a state (0.70 correlation coefficient), but this correlation is weaker for the average share of Twitter visits among Twitter users (0.59 correlation coefficient). This implies that the variation in our measure comes primarily from the extensive rather than the intensive margin.

[11] We prefer the new versus experienced classification to the incumbent versus 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, and greater coverage by media). Our classification captures the short- as well as the long-term incumbency advantage an experienced politician holds.

[12] 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 politician to access a new and relatively inexpensive channel of communication with his or her constituency. For donors who do not know about a candidate or are uninformed about his or 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.

[13] Note that our baseline empirical specification is more saturated. To construct this figure, we use practically raw data for the purpose of illustration.

[14] In this paper, we present the baseline results for a specification both without and with controls in which state-level controls interacted with being on Twitter are included.

[15] Note that the difference-in-differences analysis with staggered adoption was recently used in several papers, including Athey and Imbens (2018) and Xiong et al. (2019), who provide a more general discussion related to this approach.

[16] Technically, it is as follows:

$$\textbf{Assumption 2.} \begin{cases} \operatorname{corr}(OnTwitter_{it}, \varepsilon_{it}|X_{it}, \gamma_{pm}) = 0, \\ \operatorname{corr}(OnTwitter_{it} \times Penetration_{st}, \varepsilon_{it}|X_{it}, \gamma_{pm}) = 0. \end{cases}$$

[17] More formally, let us assume that there is some other unmeasurable activity a_{it} that happens during the same time as joining Twitter such that $\operatorname{corr}(a_{it}, \varepsilon_{it}) \neq 0$, but $\operatorname{corr}(a_{it} \times Penetration_{it}, \varepsilon_{it}) = 0$ (i.e., Assumption 1 still holds). As before, we estimate $Outcome_{it} = \beta_0 + \beta_1(TrueTwitter_{it} + a_{it}) + \beta_2(TrueTwitter_{it} + a_{it}) \times Penetration_{it} + \gamma_{pm} + \varepsilon_{it}$, where $TrueTwitter_{it}$ is a quasi-random component of joining Twitter. Then the estimated coefficients are given by

$$E\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \dots \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \dots \end{pmatrix} + (X'X)^{-1} \begin{pmatrix} E(\varepsilon_{it}|\gamma_{pm}) \\ \operatorname{cov}(OnTwitter_{it} + a_{it}, \varepsilon_{it}|\gamma_{pm}) \\ \operatorname{cov}([OnTwitter_{it} + a_{it}] \\ \times Penetration_{st}, \varepsilon_{it}|\gamma_{pm}) \\ \dots \end{pmatrix}.$$

Thus, β_1 would be biased, whereas β_2 would not.

[18] We thank the associate editor for suggesting this point.

[19] Another potential problem with estimates of the aggregate effect is that they are based on linear interpolation to the markets with zero penetration. Although doing this seems reasonable for the earlier years, it could be problematic for the later years in our time period.

[20] In Table A16 in Online Appendix A, as an illustration, we provide the coefficients of the interactions with controls and add the controls one by one for log(*amount of donations*).

[21] Note that these results should be interpreted with caution because, under Assumption 1, we cannot consistently estimate the direct effect. Moreover, because we do not observe markets with zero penetration in the data, interpreting the direct effect as one in a market with zero penetration is based on interpolation.

[22] Note that the direct coefficient for joining Twitter is marginally significant for experienced politicians, though it loses the significance and changes its sign once controls are added.

[23] We find that our placebo tests related to campaign expenditures for new politicians are still valid for an eight-week window specification, after which they fail consistently. Hence, the assumption of quasi-random entry on Twitter appears to be still plausible in this window.

[24] Note that this approach delivers results quantitatively similar to our baseline results (Table 3) if we focus on a two-week window instead of an eight-week window, so our two approaches are consistent with each other. We provide the results with various window lengths in Tables 4–7 using a preperiod of eight weeks and then varying the window length after.

[25] Comparing the 25th percentile with the 75th percentile corresponds to a comparison of median penetration below the median versus median penetration above the median, which is in line with the descriptive evidence in Figure 3. Using the same approach, we can compute the differential effects for other pairs of percentiles.

[26] The average total donations received by a House candidate over a two-year campaign are \$386,877 and \$143,611 for donations of less than \$1,000.

[27] The average total donations to a new House candidate over a two-year campaign are \$249,810 and \$94,849 for donations of less than \$1,000.

[28] In Section A.2 of Online Appendix A, we compute tests based on methods proposed by Altonji et al. (2005) to quantify how large the

impact of unobservables would have to be relative to selection on observables in order to fully explain our results. Using this approach, we find that to attribute our entire difference-in-differences estimates to selection effects, selection on unobservables would have to be at least 10.4 times greater than the selection on observables and, on average, more than 47 times greater. This strengthens confidence in our estimates. The coefficient ratio tests are provided in Table A1 in Online Appendix A for a variety of specifications.

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

[30] We also checked for politicians' Facebook account opening dates. We find that only three politicians in our sample opened a Facebook account in the same week of and only nine opened a Facebook account within four weeks of opening a Twitter account. Therefore, opening a Facebook account does not seem to be coordinated with opening a Twitter account in time. Moreover, we find no robust relationship between having a Facebook account before opening a Twitter account, as reported in Table A13 in Online Appendix A.

[31] We also checked that our baseline results are robust to the inclusion of any of the placebo variables as controls instead of running placebos. Results are available on request.

[32] The difference between the aggregate donations from new and repeat donors is statistically significant in a seemingly unrelated framework for all and new politicians but not for the experienced politicians. We report the associated *p*-values in the Table 10 notes.

[33] The results reported in Table A23 of Online Appendix A demonstrate that our Twitter findings hold more generally. Looking at the interaction effect between Facebook penetration and Facebook adoption shows a statistically significant increase in the amount and number of weekly donations, and this effect holds at the 1% level of statistical significance, though only for new politicians and not for experienced ones. 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 adoption on political donations.

[34] In these estimations, the sample of politicians who joined Facebook before Twitter is relatively small. Thus, in these results, we cluster only at the state level because in this restricted sample we do not have enough clusters to compute standard errors. We control for week fixed effects instead of week-of-month fixed effects to ensure that standard errors could be computed. Because of power issues, we focus on the full sample.

[35] These estimates are very similar without controlling for interactions of being on Twitter with market size and income.

[36] It is computationally challenging to estimate the triple interaction specification with standard errors clustered two ways at state and week levels, so despite our relatively large data set, we feel that we might face power issues here.

[37] Note that it is computationally challenging to estimate the triple interaction specification with standard errors clustered two ways, at both state and week levels. Thus, despite the large data set that we have, the confidence intervals can be quite large.

This is a strong condition that holds if the so-called precise timing assumption is satisfied, that is, if other potential determinants of the outcome of interest move smoothly around the time of a discrete change in Twitter entry (see also Gentzkow et al. (2011) for this argument applied to newspapers entering the market). However, some unobserved high-frequency campaign activity could violate this assumption.

References

Acemoglu D, Hassan TA, Tahoun A (2017) The power of the street: Evidence from Egypt's Arab Spring. *Rev. Financial Stud.* 31(1):1–42.

Aghion P, Bloom N, Blundell R, Griffith R, Howitt P (2005) Competition and innovation: An inverted-u relationship. *Quart. J. Econom.* 120(2):701–728.

Altonji JG, Elder TE, Taber CR (2005) Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *J. Political Econom.* 113(1):151–184.

Ansolabehere S, Snyder JM (2000) Old voters, new voters, and the personal vote: Using redistricting to measure the incumbency advantage. *Amer. J. Political Sci.* 44(1):17–34.

Ansolabehere S, Lessem R, Snyder JM (2006a) The orientation of newspaper endorsements in US elections, 1940–2002. *Quart. J. Political Sci.* 1(4):393–404.

Ansolabehere S, Snowberg EC, Snyder JM (2006b) Television and the incumbency advantage in US elections. *Legislative Stud. Quart.* 31(4):469–490.

Athey S, Imbens GW (2018) *Design-based analysis in difference-in-differences settings with staggered adoption*. NBER Working Paper 24963, National Bureau of Economic Research, Cambridge, MA.

Baumgartner JC, Morris JS (2010) Who wants to be my friend? Obama, youth and social networks in the 2008 campaign. Hendricks JA, Denton R, eds. *Communicator-in-Chief: How Barack Obama Used New Media Technology to Win the White House* (Lexington, Plymouth, UK), 51–66.

Besley T, Persson T, Sturm DM (2010) Political competition, policy and growth: Theory and evidence from the US. *Rev. Econom. Stud.* 77(4):1329–1352.

Bollinger BK, Cohen MA, Lai J (2013) Measuring asymmetric persistence and interaction effects of media exposures across platforms. Preprint, submitted October 11, https://ssrn.com/abstract=2342349.

Boyd D, Marwick A (2011) Social privacy in networked publics: Teens' attitudes, practices, and strategies. *A Decade in Internet Time: Symposium on the Dynamics of the Internet and Society* (International Communication Association, Boston).

Boyd DM, Ellison NB (2010) Social network sites: Definition, history, and scholarship. Donelan H, Kear K, Ramage M, eds. *Online Communication and Collaboration: A Reader* (Routledge, Abingdon, UK), 261–281.

Campante FR, Durante R, Sobbrio F (2013) Politics 2.0: The multifaceted effect of broadband Internet on political participation. *J. Eur. Econom. Assoc.* 16(4):1094–1136.

Carson JL, Engstrom EJ, Roberts JM (2007) Candidate quality, the personal vote, and the incumbency advantage in Congress. *Amer. Political Sci. Rev.* 101(2):289–301.

Chiang C-F, Knight B (2011) Media bias and influence: Evidence from newspaper endorsements. *Rev. Econom. Stud.* 78(3): 795–820.

Clarke P, Evans SH (1983) *Covering Campaigns: Journalism in Congressional Elections* (Stanford University Press, Palo Alto, CA).

Cox GW, Katz JN (1996) Why did the incumbency advantage in US House elections grow? *Amer. J. Political Sci.* 40(2):478–497.

Culotta A, Cutler J (2016) Mining brand perceptions from twitter social networks. *Marketing Sci.* 35(3):343–362.

DellaVigna S, Gentzkow M (2010) Persuasion: Empirical evidence. *Annual Rev. Econom.* 2(1):643–669.

DellaVigna S, Kaplan ED (2007) The Fox News effect: Media bias and voting. *Quart. J. Econom.* 122(3):1187–1234.

Eisensee T, Strömberg D (2007) News droughts, news floods, and US disaster relief. *Quart. J. Econom.* 122(2):693–728.

Engelberg JE, Parsons CA (2011) The causal impact of media in financial markets. *J. Finance* 66(1):67–97.

Enikolopov R, Makarin A, Petrova M (2020) Social media and protest participation: Evidence from Russia. *Econometrica* 88(4): 1479–1514.

Enikolopov R, Petrova M, Zhuravskaya E (2011) Media and political persuasion: Evidence from Russia. *Amer. Econom. Rev.* 101(7):3253–3285.

Fang L, Peress J (2009) Media coverage and the cross-section of stock returns. *J. Finance* 64(5):2023–2052.

Ferraz C, Finan F (2011) Electoral accountability and corruption: Evidence from the audits of local governments. *Amer. Econom. Rev.* 101(4):1274–1311.

Fudenberg D, Tirole J (1985) Preemption and rent equalization in the adoption of new technology. *Rev. Econom. Stud.* 52(3): 383–401.

Fudenberg D, Gilbert R, Stiglitz J, Tirole J (1983) Preemption, leapfrogging and competition in patent races. *Eur. Econom. Rev.* 22(1):3–31.

Galasso V, Nannicini T (2011) Competing on good politicians. *Amer. Political Sci. Rev.* 105(1):79–99.

Gal-Or E, Geylani T, Yildirim P (2012) The impact of advertising on media bias. *J. Marketing Res.* 49(1):92–99.

Gans JS, Goldfarb A, Lederman M (2016) Exit, tweets, and loyalty. Working paper, University of Toronto, Toronto.

Garcia-Jimeno C, Yildirim P (2015) Matching pennies on the campaign trail: An empirical study of senate elections and media coverage. Working paper, University of Pennsylvania, Philadelphia.

Gentzkow M, Shapiro JM, Sinkinson M (2011) The effect of newspaper entry and exit on electoral politics. *Amer. Econom. Rev.* 101(7):2980–3018.

Gentzkow M, Shapiro JM, Sinkinson M (2014) Competition and ideological diversity: Historical evidence from US newspapers. *Amer. Econom. Rev.* 104(10):3073–3114.

Gerber AS, Green DP (2000) The effects of canvassing, telephone calls, and direct mail on voter turnout: A field experiment. *Amer. Political Sci. Rev.* 94(03):653–663.

Goh K-Y, Hui K-L, Png IP (2011) Newspaper reports and consumer choice: Evidence from the Do Not Call Registry. *Management Sci.* 57(9):1640–1654.

Goldenberg EN, Traugott MW (1980) Congressional campaign effects on candidate recognition and evaluation. *Political Behav.* 2(1):61–90.

Gong S, Zhang J, Zhao P, Jiang X (2017) Tweeting as a marketing tool: A field experiment in the TV industry. *J. Marketing Res.* 54(6):833–850.

Gordon BR, Hartmann WR (2013) Advertising effects in presidential elections. *Marketing Sci.* 32(1):19–35.

Gordon BR, Hartmann WR (2016) Advertising competition in presidential elections. *Quant. Marketing Econom.* 14(1):1–40.

Gordon BR, Lovett MJ, Shachar R, Arceneaux K, Moorthy S, Peress M, Rao A, Sen S, Soberman D, Urminsky O (2012) Marketing and politics: Models, behavior, and policy implications. *Marketing Lett.* 23(2):391–403.

Gueorguieva V (2008) Voters, Myspace, and Youtube: The impact of alternative communication channels on the 2006 election cycle and beyond. *Soc. Sci. Comput. Rev.* 26(3):288–300.

Hoffman DL, Fodor M (2010) Can you measure the ROI of your social media marketing? *MIT Sloan Management Rev.* 52(1): 41–49.

Hong S, Nadler D (2011). Does the early bird move the polls?: The use of the social media tool Twitter by US politicians and its impact on public opinion. Bertot J, Chun SA, Reyes LFL, Atluri V, eds. *Proc. 12th Annual Internat. Digital Government Res. Conf.: Digital Government Innovation Challenging Times* (ACM), 182–186.

Jacobsen GC (1987) The marginals never vanished: Incumbency and competition in elections to the US House of Representatives, 1952–1982. *Amer. J. Political Sci.* 31(1):126–141.

Jacobson GC, Kernell S (1982) Strategy and choice in the 1982 congressional elections. *PS Political Sci. Politics* 15(3):423–430.

Jensen R, Oster E (2009) The power of TV: Cable television and women's status in India. *Quart. J. Econom.* 124(3):1057–1094.

Johnson TJ, Perlmutter DD (2010) Introduction: The Facebook election. *Mass Comm. Soc.* 13(5):554–559.

Kalogeropoulos A (2017) Following politicians in social media. Report, Reuter Institute for the Study of Journalism, University of Oxford, Oxford, UK.

Kinder-Kurlanda K, Weller K, Zenk-Moltgen W, Pfeffer J, Morstatter F (2017) Archiving information from geotagged tweets to promote reproducibility and comparability in social media research. *Big Data Soc.* 4(2):1–14.

Kumar V, Bhaskaran V, Mirchandani R, Shah M (2013) Creating a measurable social media marketing strategy: Increasing the value and ROI of intangibles and tangibles for hokey pokey. *Marketing Sci.* 32(2):194–212.

Kushin MJ, Yamamoto M (2010) Did social media really matter? College students' use of online media and political decision making in the 2008 election. *Mass Comm. Soc.* 13(5):608–630.

La Ferrara E, Chong A, Duryea S (2012) Soap operas and fertility: Evidence from Brazil. *Amer. Econom. J. Appl. Econom.* 4(4): 1–31.

Laroche M, Habibi MR, Richard M-O (2013) To be or not to be in social media: How brand loyalty is affected by social media? *Internat. J. Inform. Management* 33(1):76–82.

Lassen DS, Brown AR (2010) Twitter: The electoral connection? *Soc. Sci. Comput. Rev.* 29(4):419–436.

Levitt SD, Wolfram CD (1997) Decomposing the sources of incumbency advantage in the US House. *Legislative Stud. Quart.* 22(1):45–60.

Ma L, Sun B, Kekre S (2015) The squeaky wheel gets the grease - an empirical analysis of customer voice and firm intervention on Twitter. *Marketing Sci.* 34(5):627–645.

Marwick AE, Boyd D (2011) I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media Soc.* 13(1):114–133.

Metaxas PT, Eni M (2012) Social media and the elections. *Science* 338(6106):472–473.

Metzgar E, Maruggi A (2009) Social media and the 2008 US presidential election. *J. New Comm. Res.* 4(1):141–165.

Myerson RB (1993) Incentives to cultivate favored minorities under alternative electoral systems. *Amer. Political Sci. Rev.* 87(4):856–869.

Naylor RW, Lamberton CP, West PM (2012) Beyond the "like" button: The impact of mere virtual presence on brand evaluations and purchase intentions in social media settings. *J. Marketing* 76(6):105–120.

Nelson P (1974) Advertising as information. *J. Political Econom.* 82(4):729–754.

Pei Z, Pischke J-S, Schwandt H (2019) Poorly measured confounders are more useful on the left than on the right. *J. Bus. Econom. Statist.* 37(2):205–216.

Pennebaker JW, Boyd RL, Jordan K, Blackburn K (2015) The development and psychometric properties of LIWC2015 (University of Texas at Austin, Austin, TX).

Persson T, Tabellini G, Trebbi F (2003) Electoral rules and corruption. *J. Eur. Econom. Assoc.* 1(4):958–989.

Prat A (2002) Campaign advertising and voter welfare. *Rev. Econom. Stud.* 69(4):999–1017.

Prior M (2006) The incumbent in the living room: The rise of television and the incumbency advantage in US House elections. *J. Politics* 68(3):657–673.

Qin B (2013) Chinese microblogs and drug quality. Working paper, Hong Kong University, Hong Kong.

Qin B, Strömberg D, Wu Y (2017) Why does China allow freer social media? Protests versus surveillance and propaganda. *J. Econom. Perspectives* 31(1):117–140.

Rosenthal H, Sen S (1969) Candidate selection and voting behavior in France. *Public Choice* 6(1):71–92.

Rosenthal H, Sen S (1973) Electoral participation in the French Fifth Republic. *Amer. Political Sci. Rev.* 67(1):29–54.

Rosenthal H, Sen S (1977) Spatial voting models for the French Fifth Republic. *Amer. Political Sci. Rev.* 71(4):1447–1466.

Rotesi T (2019) The impact of Twitter on political participation. Working paper, Bocconi University, Milan, Italy.

Seiler S, Yao S, Wang W (2017) Does online word of mouth increase demand? (And how?) Evidence from a natural experiment. *Marketing Sci*. 36(6):838–861.

Smith A (2011) *Why Americans Use Social Media* (Pew Internet & American Life Project, Washington, DC).

Smith A, Rainie L (2008) The Internet and the 2008 election (Pew Internet & American Life Project, Washington, DC).

Snyder JM Jr, Strömberg D (2010) Press coverage and political accountability. *J. Political Econom.* 118(2):355–408.

Soberman D, Sadoulet L (2007) Campaign spending limits and political advertising. *Management Sci.* 53(10):1521–1532.

Spenkuch JL, Toniatti D (2016) Political advertising and election outcomes. Preprint, submitted April 1, https://ssrn.com/abstract=2613987.

Strömberg D (2004) Mass media competition, political competition, and public policy. *Rev. Econom. Stud.* 71(1):265–284.

Towner TL, Dulio DA (2012) New media and political marketing in the United States: 2012 and beyond. *J. Political Marketing* 11(1–2): 95–119.

Urban C, Niebler S (2014) Dollars on the sidewalk: Should US presidential candidates advertise in uncontested states? *Amer. J. Political Sci.* 58(2):322–336.

Virk AS (2011) Twitter: The strength of weak ties. *University Auckland Bus. Rev.* 13(1):19.

Xiang Y, Sarvary M (2007) News consumption and media bias. *Marketing Sci.* 26(5):611–628.

Xiong R, Athey S, Bayati M, Imbens G (2019). Optimal experimental design for staggered rollouts. Preprint, submitted November 9, https://arxiv.org/abs/1911.03764.

Yildirim P, Gal-Or E, Geylani T (2013) User-generated content and bias in news media. *Management Sci.* 59(12):2655–2666.

Zhang W, Johnson TJ, Seltzer T, Bichard SL (2010) The revolution will be networked the influence of social networking sites on political attitudes and behavior. *Soc. Sci. Comput. Rev.* 28(1):75–92.

Zhu Y, Dukes A (2015) Selective reporting of factual content by commercial media. *J. Marketing Res.* 52(1):56–76.