Review of Accounting Studies (2023) 28:658–688
https://doi.org/10.1007/s11142-021-09651-3

Social media, signaling, and donations: testing the financial returns on nonprofits' social media investment

Erica E. Harris[1] · **Daniel G. Neely**[2] · **Gregory D. Saxton**[3]

Accepted: 11 September 2021 / Published online: 16 November 2021

Abstract

Social media outlets provide nonprofit organizations the opportunity of opening new communication and disclosure channels. Organizations must decide whether to set up these channels. They—and in turn their target audiences—must also decide how much to use social media. In this study, we test a novel multi-level signaling theory framework to examine the relationship between social media investments and financial returns. Employing both cross-sectional and cross-temporal samples of 427 of the largest US nonhospital charities, we examine the association between donations and three dimensions of organizations' social media efforts: (1) whether the organization has a social media presence, (2) how much the organization uses social media, and (3) the level of engagement of the organization's audience. The findings support our conjecture that financial returns result from establishing a particular communication channel, from using that channel, and from having channel-specific audience engagement. We also consider how our three social media signaling dimensions condition the core donations demand variables, finding that social media substitutes for traditional fundraising expenditures. These results carry implications for the signaling and donation demand literatures and further the understanding of how new media are changing donor engagement.

Keywords Charities · Donations · Nonprofits · Signaling theory · Social media

✉ Gregory D. Saxton
gsaxton@yorku.ca

Erica E. Harris
erharris@fiu.edu

Daniel G. Neely
neely@uwm.edu

1 School of Accounting, Florida International University, Miami, FL, USA

2 Lubar School of Business, University of Wisconsin – Milwaukee, Milwaukee, WI, USA

3 Accounting Area, Schulich School of Business, York University, Toronto, ON, Canada

JEL Codes M41 · L30 · D64 · D60

1 Introduction

Nonprofit organizations are investing in social media. They are tweeting, pinning, posting, sharing, connecting, commenting, and liking in the hope these activities will help them advance their missions and achieve financial success (Waters 2011; Zorn et al. 2013). Notable financial returns have been documented for individual social media campaigns (Saxton and Wang 2014), such as 2014's #IceBucketChallenge, which went viral on Facebook and ultimately raised over $100 million (Vaidya 2014) for Amyotrophic Lateral Sclerosis (ALS) research. Yet such occurrences may be tantamount to winning the lottery. For many organizations, the investment in staff and time may not yield any notable donations, and even when donations roll in, the money may simply replace funds from traditional fundraising campaigns or donation websites. In short, while evidence suggests that social media spurs donors to give, it is unknown whether an overall positive effect on donations exists.

While much remains unknown in the nonprofit context, capital markets studies document the ability of social media to decrease information asymmetries (Blankespoor et al. 2014) and increase stock returns and market valuation (Yu et al. 2013). Building on these studies, we seize the unique opportunities presented by social media communication channels in the nonprofit organization context to test a signaling theory (Spence 1973) explanation of the relationship between social media use and aggregate financial results.

The nonprofit sector is an especially rich setting in which to study the effects of social media use. First, the sector provides goods and services critical to the success of communities and economies the world over. In the United States, for example, the nonprofit sector contributes an estimated $985.4 billion to the economy, representing 5.4 percent of GDP and playing a crucial role in the health care, education, and arts industries (McKeever 2018). To perform this vital societal work, nonprofits increasingly rely on social media, yet little is known about the effectiveness of this communication tool for charitable work (Saxton and Waters 2014).

Second, we know that much greater variation exists in nonprofits' adoption of social media, compared to that of commercial enterprises. Our study of the largest U.S. charities documents that at least 7 percent of them fail to use any type of social media, with a significant percentage absent from Facebook (19 percent) and Twitter (14 percent). This variation allows us to test whether there is an association between social media use and donor contributions, a facet of social media use virtually untestable in the for-profit sector, given large corporations' near-universal adoption (Nelson 2019).

Third, while the investment literature finds that social media use and intensity has boosted for-profit financial outcomes (Jung et al. 2018; Elliott et al. 2018), reasons exist for why this may not be the case in the nonprofit sector. To start, donations prompted by social media communication may simply be diverted from traditional fundraising. Moreover, unlike for-profit companies, which are largely focused on maximizing shareholder value, nonprofits are focused on advancing their mission and therefore communicate differently with their stakeholders (Waters 2011). That is, nonprofits' use of social media appears to serve the dual purpose of increasing engagement with programs and raising funds.

Capitalizing on this unique setting, we examine the relationship between social media use and donations by developing and testing a signaling theory-based framework covering three dimensions of nonprofits' social media communication: presence, effort, and engagement. We argue that, through the adoption of social media (presence), the sending of more frequent social media messages (effort), and the receipt of more frequent audience reactions to those messages (engagement), organizations are signaling qualities that conform to donor preferences for maximizing impact, status, and relationships. Organizations with greater signaling presence, effort, and engagement on social media will thus broaden and deepen ties to their donors and accrue greater total financial returns in the form of public contributions.

We test our arguments using cross-sectional and time-series data from 2009 to 2016 on 427 of the largest nonhospital charities in the 2013 Statistics of Income dataset. We find that all three dimensions of social media use—presence, effort, and engagement—have a positive association with donations. In so doing, we make several contributions to the literature. Our first and broadest contribution is documenting an association between nonprofits' use of social media and aggregate financial returns. Given the considerable financial- and time-related investments in social media (Hoffman and Fodor 2010), this issue is important for organizations intending to be as mission-effective as possible (Zorn et al. 2013).[1]

Second, we extend the traditional donations demand model (Weisbrod and Dominguez 1986) that posits donations as a function of efficiency, quality, and fundraising. *Efficiency* is a measure of the "price" of donations that approximates the cost to the donor to buy one dollar of the nonprofit's programmatic output, *quality* is proxied by the age of the organization, and an informational or advertising role is filled by *fundraising expenses*. With dozens of follow-up studies testing the incremental effect of additional financial, reporting, or governance variables (e.g., Balsam and Harris 2018; Petrovits et al. 2011; Yetman and Yetman 2013), the Weisbrod and Dominguez (1986) donations demand model has provided the accounting literature with a well-established baseline model showing donations accrue to more efficient and higher-quality organizations that spend more on fundraising. Our aim is to see whether social media signaling is associated with charitable giving beyond these existing explanations. To do so, we extend the base donations demand model in three ways. The first extension is by testing the incremental effect of our social

[1] The chief investment is concentrated in the personnel cost to initiate and maintain a social media presence. The cost of personnel can be classified as fundraising expense, program expense, or management and general expense on the Form 990. Since most social media presence involves a discussion of programmatic activity and broad stakeholder engagement efforts rather than direct fundraising (e.g., Guo and Saxton 2014; Waters 2011), we expect only a small portion of social media investment to be classified as fundraising expenses. We confirmed this expectation with a partner at a local CPA firm specializing in nonprofits, who noted that staff time dedicated to social media would typically be allocated between program expenses and administrative expenses. The exception would be a development person using social media as a part of their time spent on fundraising.

media signaling measures. Second, we extend the model by examining how social media signaling conditions the effects of the three core donations covariates: efficiency, quality, and fundraising. Third, we examine how social media use is leveraged differently by service-oriented and donations-oriented nonprofits.

Finally, our study responds to recent calls for research that explores social media use in different settings and incorporates communication-focused explanations of accounting phenomena (Blankespoor 2018). Our findings suggest social media outlets are best understood as *communication* channels through which charities can engage with stakeholders and grow their donor base. This requires new approaches both for organizations attempting to interact with their stakeholders and for scholars seeking to understand these new modes of interaction.

In the next section, we review the literature and set up our hypotheses. Methods and results follow. We conclude by discussing our study's implications for accounting research.

2 Theory and hypotheses

A broad and growing interdisciplinary literature is delivering substantial evidence on how nonprofits use social media to communicate with stakeholders (Guo and Saxton 2014; Waters 2011; Zorn et al. 2013). However, there is little evidence to date on the outcomes of social media usage. Evidence is particularly thin in terms of arguably the most important outcome: donations. This is surprising, given that both anecdotal and academic research exists that suggests such a link may exist. Popular press has brought to light campaigns such as the ALS #IceBucketChallenge (Vaidya 2014) and other high-profile cases that support the ability of social media to drive individual donations. Academic research, in turn, provides evidence of the success of individual social media-driven fundraising campaigns on such crowdfunding sites as Kickstarter or Indiegogo (Mollick and Nanda 2015; Saxton and Wang 2014).

However, beyond evidence from specific social media campaigns, the literature has yet to address whether an aggregate financial return on social media investment exists. It is plausible that the donations raised via social media efforts simply substitute for existing fundraising channels. In a worst-case scenario, decreased donations from other online and offline venues may not be offset by higher social media-driven donations.[2] In effect, the more important question is not whether social media leads to specific campaign donations but whether social media is associated with higher

[2] For example, donors who are prompted to give by the organization's social media communication may be targeted by the organization's other fundraising venues, such as websites, email, mailouts, or in-person fundraisers. In that scenario, the social media efforts are not capturing any new donations. In a worst-case scenario, those same donors could decide to give less when they are motivated to give from social media than when they are spurred to give by an in-person meeting, a gala fundraiser, or an email. We also note our model is not concerned with the specific vehicle through which money is donated; in our explanation, it does not matter whether the donor gives through social media or via a third-party app, a website, a text, social media, or in person. Money donated through all sources will show up in our empirical donations dependent variable.

overall donations. This question has yet to be addressed in the literature, and we therefore dedicate our study to understanding this relationship.

The Weisbrod and Dominguez (1986) donations demand model, focusing on the key roles of quality, efficiency, and fundraising, provides accounting scholars with a baseline model for explaining aggregate charitable donations (e.g., Gordon et al. 2009; Harris and Neely 2016; Petrovits et al. 2011).[3] We build on this model by incorporating a signaling theory framework (Spence 1973) to understand the association between social media investment and donations. While many variants of the donations demand model incorporate a signaling perspective (e.g., Saxton et al. 2014), the literature is not equipped to fully explain the effects of communicating via social media.

For one, existing studies focus on performance metrics or third-party ratings derived from formal reporting by nonprofit organizations (Harris and Neely 2016; Tinkelman 1999). The result is a heavy emphasis on the one-way relay of performance-related information. In contrast, social media allows for informal and two-way communication with stakeholders (Cade 2018). In the highly interactive, personalized, and networked context of social media, organizations can go beyond the disclosure of financial performance to signal a range of donor-relevant characteristics, such as the organization's transparency, accountability, relationship-building orientation, communicativeness, values, or trustworthiness—qualities that are more difficult to convey via traditional reporting channels (Hetze 2016). Some nonprofit literature does distinguish financial from nonfinancial information (Saxton et al. 2014), but that binary distinction does not fully capture the complexity and breadth of communication via social media networks.

Second, social media is a substantially more dynamic communicative environment (Blankespoor et al. 2014), with configurations of friend and follower and discussion networks changing not annually but daily. Most relevant from an organizational signaling perspective is that we can capture the variation in the day-to-day effort expended by organizations via the brief discrete messages sent to followers (Waters 2011).

Third, both capital markets (e.g., Richardson and Welker 2001) and donations studies (e.g., Harris and Neely 2016) focus on the financial effects of organizational signals, yet the relationship between signals (especially disclosure-based signals) and market response is largely indirect. In part due to the difficulty in identifying relevant, observable, and quantifiable signal-based reactions, the literature has little conceptualization or direct examination of actual *countersignals* (Connelly et al. 2011) or the responsive feedback sent to organizations from message receivers, which on social media are publicly visible and directly linked to specific messages in the form of likes, comments, and shares (Saxton and Waters 2014).

[3] The accounting literature explaining donations generally incorporates one or more new variables into the baseline donations demand model, thereby testing the incremental effect of such concepts as third-party ratings (Gordon et al. 2009), accounting information quality (Yetman and Yetman 2013), internal control deficiencies (Petrovits et al. 2011), or CEO pay (Balsam and Harris 2014).

In sum, current signaling theory and donations demand literatures collectively leave us without a means of readily capturing how the nuances of the social media context may influence aggregate donations demand. For this reason, we integrate signaling theory (Spence 1973) into the donations demand model, with our signaling theory-driven hypotheses describing the effects of social media on public contributions. Our premise is that donors will gravitate to organizations that signal the ability and willingness to maximize donor preferences for three things: community impact (Harris and Neely 2016; Tinkelman 1999), personal status (Bénabou and Tirole, 2006; Wallace et al. 2020), and meaningful relationships with the organization or its stakeholders (Croson et al. 2009; Sargeant 2003). We argue that the extent of nonprofits' social media use can signal otherwise unobservable organizational qualities that appeal to these three donor preferences. In the following sections, we present our hypotheses on the association of social media presence, effort, and engagement with donor support as well as the conditioning effects of these factors on the traditional donations demand model.

2.1 Social media presence: the channel selection decision

Social media platforms, such as LinkedIn (2003), Facebook (2004), YouTube (2005), Twitter (2006), Instagram (2010), and Pinterest (2010), have multiplied over the last decade and a half. These platforms have vast audiences of users, with 367 million on Pinterest, 326 million on Twitter, 645 million on LinkedIn, 1 billion on Instagram, 397 million on SnapChat, 694 million on China's Tencent QQ, and over 2.6 billion on Facebook (Statista 2020). What is striking, from a theoretical perspective, is how social media presents an opportunity for a multitude of new communication and disclosure channels.

The decision to create a signaling channel, one of the fundamental elements of any communication act (Lasswell 1948), is largely unexamined in the signaling theory literature. In the capital markets disclosure literature, in contrast, development of new information technologies has prompted scholars to examine the market effects of setting up and using a variety of new technological platforms and channels, including XBRL (Hodge et al. 2004), online video (Elliott et al. 2012), websites (Debreceny et al. 2002), and blogs (Campbell et al. 2019). Most recently, social media has been found to decrease information asymmetries around earnings announcements (Blankespoor et al. 2014), mitigate reputational damage in the aftermath of product recalls (Lee et al. 2015), and boost stock returns (Yu et al. 2013) and market valuations (Du and Jiang 2015).

Along the same lines, we expect nonprofit organizations use social media to signal key donor-relevant characteristics that help reduce information asymmetries and lead to higher contributions. Building on findings that creating a website signals product and brand quality (Basoglu and Hess 2014), we argue that creating a social media account appeals to donors' preferences for maximizing impact by signaling an organization's quality. Moreover, in the nonprofit setting, charitable donations typically have low visibility (Bénabou and Tirole 2006), unless the organization announces donor giving; social media adoption therefore appeals to donors' status-maximizing preferences in signaling the organization's increased capacity to publicly recognize donor efforts. Furthermore, adopting social media channels send signals that new classes of donors, particularly social media's younger donor base (Flannery et al. 2009), are worthy of managerial attention; this signals an open, engaged community orientation (Fischer and Reuber 2011) that is relevant to donors who prefer having a relationship with the organization or its stakeholders.

In sum, setting up social media accounts sends initial signals of the organization's potential for impact, of its sensitivity to donors' wishes to signal their status, and of its relational orientation. We therefore argue that sample organizations that have created social media accounts, such as Teach for America, Brother's Brother Foundation, or National Public Radio, are sending stronger signals to donors than organizations, such as the Alliance for Sustainable Energy, which have not and are therefore conveying a lack of interest in such signals. Further, we argue a nonprofit such as Teach for America, which set up seven social media channels (Facebook, Twitter, Instagram, YouTube, Pinterest, LinkedIn, and Google+), is sending stronger signals than the Brother's Brother Foundation, which has only a Facebook account, or National Public Radio, which has established only a Twitter account. In line with the above logic, our first hypothesis argues that, the greater the social media presence achieved through setting up social media communication channels, the greater the appeal to current and potential donors and thus the stronger the association between social media and donations.

Hypothesis 1 *The amount of donations received will be positively associated with the presence of social media channels.*

2.2 Organizational effort: signaling frequency

Our second signaling dimension captures the level of organizational effort committed to these new communication channels. Specifically, the nonprofit organization must decide how much energy to expend via visual or textual messages—tweets, pins, status updates, photos, or videos—sent to followers on Twitter, Pinterest, Facebook, Instagram, and YouTube, respectively. These messages are vehicles for specific micro-signals, and unlike the relatively static annual reporting context typically examined in signaling theory studies, these dynamic signals are visible on a real-time basis through the continual live stream of organizational messages. As a result, we can capture *signaling effort* in the number of messages organizations send. Social media provides for extensive variation—with some nonprofits sending thousands of messages and others not sending even a single message over the course of the year (Saxton and Waters 2014).

We contend that the level of social media effort sends several donor-relevant signals. To start, building on analogous findings in the advertising literature, we argue more frequent organizational messages appeal to donors' impact-maximizing preferences by signaling the organization is legitimate and more productive, reliable, trustworthy, and professional than less active nonprofits (e.g., Aiken and Bousch 2006;

Amblee and Bui 2011; Cheung et al. 2014).[4] Second, in signaling the capacity and willingness to publicly promote and recognize donors' efforts, the amount of organizational messages signals the organization's ability to help boost the individual donor's social status and reputation (Glazer and Konrad 1996).[5] Lastly, organizations' social media messages can send signals relevant to donors' preferences for building relationships with the nonprofit or its stakeholder community.[6] Namely, donors with a strong preference for becoming a member of a community will be attracted by the external community orientation signaled by active organizational messaging, while donors desiring specifically a donor-donee relationship with the organization will be attracted by the traits of two-way communication, transparency, feedback, and responsiveness (Sargeant 2003) that, broadly conceived, are all signaled by high levels of organizational activity on social media.

We thus argue organizations' social media effort, as reflected in the volume of messages sent, attracts donors by sending signals relevant to donor preferences. To understand the mechanism, it is useful to think of an organization that sends few or no social media messages, such as Feed The Children, which sent 17 Facebook messages in all of 2009. Donors are unlikely to see this nonprofit as offering a high likelihood of meaningful audience engagement, nor would they see it as offering a means for publicly acknowledging their donations, volunteer efforts, or accomplishments to other Facebook users. In addition, the organization is not signaling "high quality." Organizations closer to the mean (216 messages), such as the San Diego Zoo, which sent 276 messages in 2010, are sending more robust donor-relevant signals, and even stronger signaling is being done by heavy posters, such as National Geographic, which sent 2,561 messages in 2016. Consequently, our second hypothesis posits that greater organizational effort in signaling will be associated with higher future donations.

[4] While our arguments are at the aggregate, organization-year level, it may be useful to also see how *at the message level* organizations can tap into specific donor preferences. An example of a Facebook message targeting impact maximizers is the following, sent by the Institute of International Education on October 8, 2015: "Have you had the chance to look at the one year impact report for #GenerationStudyAbroad? Here's a quick rundown of key things to know about the initiative and our 600+commitment partners." The message was accompanied by an infographic with key impact indicators. Nonnumerical examples of such messages typically show examples, data, or photos of the organization's charitable output, programs, or impacts.

[5] An example of a message relevant for status-maximizers is the following, sent by the Carle Center for Philanthropy on April 28, 2016, acknowledging a large donor: "There's no better way to say 'thank you' to our donors than with a surprise visit from some of their biggest fans! Students from Carle Auditory Oral School hopped on a bus this morning to deliver a special message of thanks to First Federal Savings Bank and GTPS Insurance Agency, the VIP sponsors of INSYNC. This premier lip-syncing contest raised more than $40,000 for Carle Auditory Oral School, and the students are giddy about everything these two businesses have made possible for their school." As in this sample post, such messages often include a photo of the donor along with some acknowledgement or recognition.

[6] For example, the following post, sent by UNICEF on January 13, 2010, carries relevance for relationship-maximizers in how the message stresses community and relationships rather than societal impact or personal status: "Help us help Haiti! Create a personal fundraising page and share it with your friends and family asking them to donate. Part of a group, school or company? Create a team page and the reach and impact become even greater."

Hypothesis 2 *The amount of donations received will be positively associated with the number of messages sent via social media channels.*

2.3 Audience engagement: public reactions as countersignals

Our third and final dimension captures audience engagement via *countersignaling,* or the public feedback to organizational signals (Connelly et al. 2011). On social media platforms such as Facebook, signals are delivered in the form of discrete messages, while countersignals are sent in the form of audience liking, commenting on, and sharing of those messages. What distinguishes these "countersignals" from other forms of consumer-generated content is that they can only come in response to discrete, identifiable organizational message-based signals.[7] Collectively, these audience responses constitute consumer-driven, or social, signals that illuminate core donor preferences.

To start, we argue that the amount of countersignaling engagement relays signals that directly bear on donors' preferences for maximizing impact; namely, the level of audience engagement generates a "collective signal of reputation" (Amblee and Bui 2011, p. 91) that influences consumers by signaling quality (Cheung et al. 2014) and generating trust (Donath 2007). Second, the volume of countersignaling engagement speaks to donor preferences for status and reputation by signaling the size of the organization's audience network and therefore how "conspicuous" (Wallace et al. 2020) future donor recognition announcements will be.[8] Lastly, the level of audience engagement signals whether the organization has a strong community orientation (Donath 2007) or an engaged stakeholder network, thus speaking to donors with strong community- and relationship-building preferences.

The effect is that, when a donor is choosing between two organizations—one with high countersignaling engagement and one with low—the high-engagement organization is more likely to attract the donor given the stronger impact, status, and relationship signals being sent. Concretely, an organization with a relatively low level of engagement, such as Colorado Gives, which received four comments, 682 likes, and 102 shares on Facebook in 2016, is less likely to attract donors that year than organizations closer to the mean (3,220 comments, 125,774 likes, and 19,731 shares) such as Be The Match, which in 2016 garnered 2,186 comments, 68,068 likes, and 28,919 shares. And at the top of the ladder, National Geographic, which

[7] Consistent with the term "countersignaling," the audience's actions are both a response to specific organizational messages (and thus *counter*signals) and, collectively, signals themselves of donor-relevant organizational characteristics. In related research, capital markets studies have considered user-generated "cashtag" tweets to be indicators of information content, investor attention, and aggregate opinion (Bartov et al. 2018; Curtis et al. 2016; Lee et al. 2015). While our "countersignals" are similarly a form of user-generated content, they are distinct in that they are linked to specific organizational messages.

[8] Also relevant here is how a donor's countersignaling engagement provides the vehicle for identity signaling and virtue signaling practices (Wallace et al. 2020): each time a donor engages by sharing, replying to, or liking a nonprofit organization's message, the individual has another opportunity to signal a prosocial identity intended to be seen favorably by others; and the larger the countersignaling network, the more salient the status-boosting signal.

received 235,595 comments, 77,101,819 likes, and 9,688,449 shares in 2015, is much more likely still to attract donors. In sum, from the organization's perspective, the more countersignals a message receives, the more effective the message is in its delivery of donor-relevant impact-, status-, and relationship-oriented signals and thus in its engagement with a broader audience of donors. We expect this higher level of engagement to be associated with a higher level of future donations. Our third hypothesis is therefore as follows.

Hypothesis 3 *The amount of donations received will be positively associated with the amount of audience countersignals received.*

2.4 Conditioning the donations demand model: interactions with age, efficiency, and fundraising

Above we have posited that social media-driven signaling adds value to traditional fundraising efforts. However, a corollary of our arguments is that social media is changing the ways nonprofit organizations communicate with their stakeholders. It is therefore plausible that setting up social media channels, pouring effort into sending messages on those channels, and receiving near real-time audience feedback via social media platforms not only adds to traditional fundraising efforts but changes how fundraising, donor demand, and charitable giving operate. If so, then traditional drivers of donor support, such as fundraising expenses or organizational efficiency and quality, may have a stronger or weaker effect, depending on the nature of an organization's social media profile. To examine this idea, in our remaining three hypotheses we consider how our social media signaling dimensions (channel presence, effort, and audience engagement) condition the core variables of the donations demand model (Weisbrod and Dominguez 1986), arguing how social media use complements or substitutes for fundraising (*Fundraising Expense*), quality (*Age*), and efficiency (*Program Ratio*).

2.4.1 Social media and fundraising expenses

While social media could complement traditional fundraising, we argue it is more likely to substitute for it. The reasoning lies in their shared communicative function. Namely, we have argued social media constitute rich communication platforms, and, in the core donations demand model, fundraising also serves a communicative purpose; specifically, advertising the quality of a nonprofit's output. In effect, both traditional fundraising and social media serve as communication channels, therefore rendering their relationship more likely substitutive. Social media also provides a cheaper and more immediate means of communicating quickly with a wider range of stakeholders (Waters 2011). Consequently, rather than providing an additional means of communicating with current and potential donors, social media may partially *replace* traditional fundraising expenses, similar to what Harris and

Ruth (2015) find in the presence of celebrity affiliations. We thus posit an inverse relationship between social media use and traditional fundraising expenditures. That is, in the presence of high levels of social media signaling, fundraising expenses will be lower than in the absence of such signaling. This culminates in our fourth hypothesis.

Hypothesis 4 *Social media presence, effort, and engagement act as substitutes for fundraising expenses in the demand for donations.*

2.4.2 Social media and quality

In contrast to fundraising, organizational quality is not a form of communication but rather a trait. We argue that social media acts as a megaphone (Gallaugher and Ransbotham 2010) that amplifies organizational characteristics. In the for-profit context, research has found the relationship between financial disclosure and cost of capital to be magnified when intellectual capital disclosures are provided (Mangena et al. 2014). In the nonprofit sector, Harris and Neely (2021) find that organizational transparency magnifies the effects of performance on future contributions. Following this logic, we expect social media will likewise highlight organizational quality, playing into donor preferences for impact and thus boosting donor support for high-quality organizations. The literature on nonprofit donations demand has established that an organization's "stock of goodwill," or its quality, is captured by the age of the organization (Weisbrod and Dominguez 1986). We therefore posit a positive association between donations and the interaction between social media and organizational quality, where age serves as a proxy for organizational quality, as follows.

Hypothesis 5 *Social media presence, effort, and engagement act as complements to organizational quality (age) in the demand for donations.*

2.4.3 Social media and efficiency

Like quality, the level of efficiency, or the proportion of expenses spent on programs, is a key impact-related organizational trait influencing the demand for donations (e.g., Petrovits et al. 2011). The literature has found that organizations receiving higher ratings, based on their financial condition, receive more contributions relative to unrated (Harris and Neely 2016) and lower-rated organizations (Gordon et al. 2009). We similarly expect social media to exhibit a complementary effect, once again serving as an amplifier for the organization's level of efficiency. This leads to our sixth and final hypothesis.

Hypothesis 6 *Social media presence, effort, and engagement act as complements to efficiency in the demand for donations.*

3 Research design

3.1 Measures

As discussed above, we employ the donations demand model developed by Weisbrod and Dominguez (1986) and widely used in the accounting literature as our base model. We then incorporate our social media test variables along with the standard donations demand model covariates discussed below and defined in Table 12 in the Appendix. Our social media test variables incorporate data gathered from seven social media outlets: Facebook, Twitter, YouTube, LinkedIn, Pinterest, Instagram, and Google+.

First, for Hypothesis 1, which concerns social media presence, we consider five alternative measures of our test variable: (1) *Social Media*, an indicator if the organization is on any one of the seven social media platforms; (2) *Facebook*, an indicator for whether the organization is on Facebook; (3) *Twitter*, an indicator for whether the organization is on Twitter; (4) *Other Social Media*, an indicator for whether the organization is on any one of the remaining five social media platforms (YouTube, LinkedIn, Pinterest, Instagram, or Google+); and (5) *Total Social Media*, a summation variable that ranges from 0 to 7 indicating the number of social media platforms the organization uses.

To address our second and third hypotheses, where we explore the extent of social media-based signaling and countersignaling, we focus on Facebook data. Facebook was chosen given that most of the sample has a Facebook account (81%) and we could obtain detailed records of the messages sent by the organization as well as the countersignals received by the organization in the form of audience comments, likes, and shares. Accordingly, our analyses of Hypothesis 2 include test variables defined as the number of *Messages* sent on Facebook, while our Hypothesis 3 analyses employ the number of audience *Comments*, *Likes*, and *Shares* of the organization's Facebook messages.[9]

Following the literature (Petrovits et al. 2011; Balsam and Harris, 2018), our control variables are measured with a one-year lag. However, our test variables are measured contemporaneously given the real-time nature of social media signaling. That is, in contrast to annual report-based studies, which require a time lag for donors to review and react to disclosure information made available (typically via IRS Form 990, which can be significantly delayed), social media information

[9] We focus on the number of messages and countersignals to test H2 and H3, given that we are interested in the amount of effort an organization puts into its social media presence as well as the extent of the constituent response to this effort. For H2, employing a measure of message frequency is supported by findings of the signaling power of the analogous measure of advertising intensity (Aiken and Boush 2006), by evidence of the resource-acquisition effects of the frequency of social interactions (Fischer and Reuber 2011), and by findings that the amount of firm-generated content drives financial value (Mumi et al. 2019). Similarly, for H3, the use of a volume measure of countersignaling is supported by the electronic word-of-mouth literature, which has substantial research suggesting that volume-based measures are more important drivers of consumer behavior than content-based measures such as sentiment/valence (Amblee and Bui 2011; Cheung et al. 2014). Given this evidence and in line with our hypotheses, we focus on volume and leave content/valence to future research.

is updated and available to constituents and potential donors 24 hours a day, seven days a week. We believe this is a distinct feature of our study given the dynamic nature of social media signaling.

Our response variable, *Donations*, is defined as the natural log sum of total indirect and direct donations received by the organization as reported on IRS Form 990.[10] Our first set of controls are the three core donations demand model variables (Weisbrod and Dominguez 1986). *Fundraising Expenses* are included in lagged, logged format.[11] *Age* is measured as the natural log of the number of years since IRS ruling. Efficiency is defined as the lagged ratio of program service expenses to total expenses, also known as the *Program Ratio*. In line with the literature, donations are expected to be increasing in all three variables (Harris and Ruth 2015; Trussel and Parsons 2007; Yetman and Yetman 2013). We also include controls for other financial and organizational characteristics found to significantly explain contributions in the nonprofit sector (Harris and Neely 2021; Saxton et al. 2014). We proxy for size using lagged logged year-end *Total Assets* and expect a positive association, consistent with the literature (Krishnan and Schauer 2000). To control for the effects of alternative revenue sources, we include lagged logged *Program Service Revenues* and *Government Grants;* however, given mixed results in this area, we do not predict the direction of these variable coefficients. Finally, we control for *Industry* and *State* fixed effects. We test our model using robust regression techniques (iteratively reweighted least squares), which assigns a weight to each observation with higher weights given to observations that meet the assumptions underlying standard multiple regression. Robust regressions also adjust for data outliers identified as a potential problem when working with IRS Form 990 data (Tinkelman and Neely 2011).

In sum, we employ the following model to test our hypotheses.

$$\begin{aligned} Donations_t = {} & \beta_1\, Social\, Media_t + \beta_2\, Fundraising\, Expenses_{t-1} + \beta_3\, Age_t \\ & + \beta_4\, Program\, Ratio_{t-1} + \beta_5 Total\, Assets_{t-1} + \beta_6\, Government\, Grants_{t-1} \\ & + \beta_7\, Program\, Service\, Revenues_{t-1} + Industry\, and\, State\, Fixed\, Effects + \varepsilon, \end{aligned}$$

where *Social Media* is alternatively defined as *Facebook*, *Twitter*, *Other Social Media*, and *Total Social Media* for our tests of social media presence (H1), *Messages* for our tests of organizational effort (H2), and *Comments*, *Likes*, and *Shares* for our tests of audience engagement (H3). Models that test hypotheses 4–6 include interactions between the three core donations demand variables—*Fundraising Expenses*, *Age*, and *Program Ratio*—and our social media presence, effort, and engagement test variables.

[10] Direct donations are those received from individual donors, while indirect donations are those received through third-party administrative organizations such as The United Way. Alternatively, we considered measuring the dependent variable as either government grants or program service revenues. However, we expect donors to be relatively more sensitive to social media usage, compared with governmental entities or stakeholders engaging nonprofits in a fee-for-service arrangement.

[11] Model results are robust to alternatively including contemporaneous *Fundraising Expenses* or both lagged and contemporaneous *Fundraising Expenses*. We use the lagged version in our main model following prior literature.

Table 1 Sample selection

Criteria	N
1500 largest (by total revenues) 501(c)3 nonprofit organizations from 2013 Statistics of Income database	1,500
Less hospital systems	(931)
Less organizations with ambiguous websites or social media pages	(49)
Less organizations with missing model variables	(93)
Total unique sample organizations	427

3.2 Sample selection

To test our hypotheses, we identified the 1500 largest (by total revenues) nonprofits in the 2013 Statistics of Income (SOI) data file, the most recent available at the commencement of our study in 2016.[12] In the spring of 2016 we searched the websites of each of the 1500 organizations to determine their social media presence. Through this process, it was noted that the social media presence identified for the hospitals in our sample often represented an entire hospital system (e.g., the sample hospital was only one of several hospitals making up a hospital system). Given that we were unable to properly match the social media activity and financial outcomes for these hospital systems, we eliminated 931 sample organizations classified as hospitals. As indicated in Table 1, after eliminating 49 additional observations with ambiguous websites or social media accounts and 93 observations missing model variables, our final sample consists of 427 unique nonprofits.

For Hypothesis 1, the social media test variables (*Social Media*, *Facebook*, *Twitter*, *Other Social Media*, and *Total Social Media*) were collected during a single point in time (2016). This allowed us to hand-collect data for seven different social media sites (Facebook, Twitter, Instagram, YouTube, Pinterest, LinkedIn, and Google+). Table 2 provides the breakdown of our 427 unique sample organizations by industry type. Of the nine industries represented, the two with the majority of organizations are universities (39%) and health (23%).

Table 3 presents descriptive statistics for our model variables. Here we note that 93 percent of the sample is using at least one of the seven social media sites examined. Twitter is the site most often represented (86%), while 81 percent use Facebook and 84 percent use any one of the other five sites. Sample organizations are employing on average four social media platforms, indicating broad social media participation. Turning to organization-specific characteristics, sample organizations have been in business for an average of 45.65 years and are quite large, reporting mean donations of $116 million and $1.8 billion in total assets. Sample organizations

[12] The Form 990 is due on the 15th day of the fifth month after the organization's year-end. The IRS allows nonprofits to extend the 990 filing deadline an additional six months. There is also a notable time lag between when a nonprofit eventually files the Form 990 and when the IRS creates and disseminates data files such as the SOI files. The result is that at the time of our study (2016) the most recent SOI file was for 2013.

Table 2 Sample Industries

Industry	N	%
Arts	15	4
Universities	165	39
Education	35	8
Environmental	3	1
Health	103	23
Human Services	34	8
International	29	7
Public and Societal Benefit	41	10
Religion	2	0
Total	427	100

Table 3 Descriptive statistics: unique observations

N = 427	Mean	Med	SD	Q1	Q3
Social Media$_t$	0.93	1.00	0.25	1.00	1.00
Facebook$_t$	0.81	1.00	0.41	1.00	1.00
Twitter$_t$	0.86	1.00	0.39	1.00	1.00
Other Social Media$_t$	0.84	1.00	0.37	1.00	1.00
Total Social Media$_t$	3.95	4.00	1.82	3.00	5.00
Donations$_t$	115,726,039	20,596,872	280,244,978	1,944,353	1,447,662,336
Fundraising Expenses$_{t-1}$	8,629,695	2,599,848	19,035,310	1	8,771,209
Age$_t$	45.65	46.00	25.21	23.00	68.00
Program Ratio$_{t-1}$	0.88	0.89	0.09	0.84	0.93
Total Assets$_{t-1}$	1,813,604,182	616,689,600	4,690,301,289	226,592,464	1,560,460,160
Gov Grants$_{t-1}$	95,139,413	2,635,150	300,682,310	1	43,829,496
Program Service Revenues$_{t-1}$	396,748,941	216,515,440	568,432,869	85,250,344	418,635,200

We present unlogged variables for ease of interpretation, but all continuous variables are logged in the multivariate tests

See Table 12 in the Appendix for variable definitions

report an average of $8.6 million in fundraising expenses and are rather efficient in their operations, with an average of 88% of their expenses directed toward programs. Finally, other revenue sources represent a significant portion of total revenues, as sample organizations report an average of $95 million in government grants and an average of $397 million in program service revenue.

Table 4 provides univariate correlations for our model variables. Consistent with hypothesis 1, we find that our *Social Media* test variable relates positively to the donations response variable. While several of our individual test variables (e.g., *Social Media* and *Twitter*) are highly correlated with each other, no two test variables are included in the same regression. We also note no problematic correlations

Table 4 Correlation matrix

N = 427	1	2	3	4	5	6	7	8	9	10	11	12
1. $Donations_t$	1.00											
2. Social $Media_t$	**0.08**	1.00										
3. $Facebook_t$	0.04	**0.53**	1.00									
4. $Twitter_t$	**0.12**	**0.67**	**0.46**	1.00								
5. Other Social $Media_t$	0.00	**0.62**	**0.40**	**0.58**	1.00							
6. Total Social $Media_t$	0.03	**0.58**	**0.47**	**0.62**	**0.73**	1.00						
7. Fundraising $Exps_{t-1}$	**0.20**	**0.25**	**0.28**	**0.27**	**0.28**	**0.34**	1.00					
8. Age_t	0.00	**0.19**	**0.20**	**0.19**	**0.18**	**0.21**	**0.37**	1.00				
9. Program $Ratio_{t-1}$	0.05	−0.04	−0.04	−0.06	**−0.11**	**−0.18**	**−0.10**	**−0.10**	1.00			
10. Total $Assets_{t-1}$	**0.22**	**0.15**	**0.13**	**0.15**	**0.17**	**0.17**	**0.35**	**0.17**	**0.15**	1.00		
11. Gov $Grants_{t-1}$	−0.01	**0.21**	**0.29**	**0.21**	**0.29**	**0.29**	**0.50**	**0.30**	**−0.12**	**0.31**	1.00	
12. Prog Service $Revs_{t-1}$	**−0.29**	−0.02	0.04	0.01	**0.08**	**0.09**	**−0.12**	**0.07**	−0.03	**0.14**	**0.15**	1.00

Bolded values are significant at the 10% level (one-tailed for the social media test variables, two-tailed for control variables)

See Table 12 in the Appendix for variable definition among the control variables, with the highest correlation coming in between *Government Grants* and *Fundraising Expenses* (0.50). Furthermore, tests of model variance inflation factors (VIFs) indicate that multicollinearity is not an issue in our sample (all variable VIFs are below 2.5).

4 Results

4.1 Tests of social media presence (H1)

Table 5 presents the results of Hypothesis 1—that the presence of social media is positively associated with the amount of contributions received. In support of our conjectures, we find that all five social media test variables are positively associated with donations, consistent with the ability of social media communication channels to increase aggregate annual donations. Specifically, we find that having a social media presence on any outlet is associated with a 61.5% higher level of donations relative to nonprofits without any social media presence.[13] Turning to model control variables, as expected, we find fundraising expenses, efficiency, and size to be positively associated with donations. We also find some evidence of crowding out of funding sources, with a negative association between donations and government grants as well as program service revenues. We fail to find any significant relationships with age.

To further isolate the finding that establishing a social media presence is positively associated with donations, we tap into a larger, time-series dataset available for Facebook from 2009 to 2016.[14] For each of the 427 unique organizations in our sample, we downloaded all available Facebook data (including all messages sent and countersignals received) for each year from 2009 to 2016.[15] Given that we are still

[13] The coefficient on a dummy variable where the dependent variable is logged can be interpreted as 100[$exp(c)$—1] where C is the coefficient estimate (Halvorsen and Palmquist 1980).

[14] 2008 is the first year organizations could create a Facebook page. Our time-series sample begins in 2009 on account of the lagged variables in our empirical model.

[15] We collect digitized Facebook data in October 2016 by using custom Python code to access the Facebook application programming interface (API). Specifically, we used the API to download all organizational messages along with the number of audience likes, shares, and comments on each organizational message. For example, for an organization that created its Facebook page in 2008 (the first year pages were implemented by Facebook), we downloaded all posts made from 2008 through 2016, along with counts of the numbers of shares, likes, and comments for each organizational message. Similarly, an organization that set up its Facebook page in 2010 would have 2010 through 2016 data on the number of posts as well as audience likes, shares, and comments. We then aggregated these data by organization/year to obtain annual counts of the number of organizational messages sent as well as the number of audience reactions (countersignals) for each organization/year. Note that the number of Facebook followers held by an organization may drive audience reactions (Saxton and Waters 2014). Yet given that an individual can like, comment, or share an organization's message without following the organization, the number of followers would provide only an indirect measure of audience engagement. In effect, our measures of audience likes, comments, and shares offer a more direct measure of message-driven countersignaling and audience engagement and thus are best suited for our tests. For this reason, we do not collect data on the number of Facebook followers.

Table 5 Cross-sectional tests of hypothesis 1: the effects of social media presence

Dependent variable: $Donations_t$	(I) $Social\ Media_t$ Coefficient *p-value*	(II) $Facebook_t$ Coefficient *p-value*	(III) $Twitter_t$ Coefficient *p-value*	(IV) $Other\ Social\ Media_t$ Coefficient *p-value*	(V) $Total\ Social\ Media_t$ Coefficient *p-value*
Constant	−22.173***	−22.089***	−21.729***	−22.049***	−22.442***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Test variable (defined in column heading)	**0.479***	**0.344****	**0.867*****	**0.450****	**0.067***
	0.055	***0.037***	***0.000***	***0.016***	***0.060***
Fundraising $expenses_{t-1}$	0.201***	0.199***	0.200***	0.202***	0.202***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Age_t	0.074	0.048	0.057	0.055	0.068
	0.475	*0.642*	*0.558*	*0.590*	*0.502*
Program $ratio_{t-1}$	2.990***	3.034***	2.848***	3.135***	3.215***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Total $assets_{t-1}$	0.811***	0.814***	0.811***	0.799***	0.811***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Gov $grants_{t-1}$	−0.021*	−0.023**	−0.022**	−0.024**	−0.021**
	0.068	*0.048*	*0.048*	*0.034*	*0.064*
Program Service $Revenues_{t-1}$	−0.093***	−0.096***	−0.093***	−0.093***	−0.095***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Industry and state fixed effects	YES	YES	YES	YES	YES
N	427	427	427	427	427
Adjusted R^2	0.3485	0.3472	0.3683	0.3551	0.3488

See Table 12 in the Appendix for variable definitions

*Significant at 10% level, **significant at 5% level, ***significant at 1% level (one-tailed for the bolded test variables, two-tailed for control variables)

Table 6 Time-series sample

Year	Firm-years	New to Facebook	Mean messages	Mean comments	Mean likes	Mean shares
2009	387	109	48	196	959	11
2010	408	51	114	589	3,175	22
2011	418	26	157	844	6,890	1,156
2012	419	50	218	1,683	38,316	5,637
2013	427	12	280	3,171	118,669	18,812
2014	417	15	310	5,284	242,066	32,793
2015	392	7	366	7,937	357,288	58,698
2016	141	3	239	11,684	470,517	83,838
Total	**3,009**	**273**	**216**	**3,220**	**125,774**	**19,731**

Table shows the number of our 427 sample organizations for which time-series data is available (*Firm-years* column) as well as the year the organization joined Facebook (*New to Facebook* column). Recall that our original sample was drawn from the 2013 SOI data, which ensured that all 427 unique organizations had financial data for 2013. In expanding our sample to the years 2009 to 2016, we lost observations in years before and after 2013, as noted above, for nonprofit organizations that did not have all necessary model data in those years. 2016 has fewer firm-year observations because of missing Form 990 data caused by the time lag in which Form 990 data are made available

interested in years during which an organization had not yet adopted Facebook and to facilitate our analyses of organizations new to Facebook, we include all firm-year data, regardless of whether an organization had adopted Facebook. As a result, the maximum firm-year observations for this extended time-series sample is 427 unique organizations for eight years or 3,416 total possible firm-years; however, missing Form 990 financial data limit the final data to 3,009 firm-year observations.[16] Table 6 summarizes our data collection efforts for this time-series data. The first column (*Firm-years*) shows the number of valid observations per year, while the second, *New to Facebook*, shows the number of organizations that joined Facebook each year. As shown in Table 6, we see the majority of organizations joining Facebook between 2009 and 2012, consistent with early adoption of this broadly used social media platform. We also provide mean messages, comments, likes, and shares over our time series sample. As expected, and consistent with prior social media literature (Saxton and Waters 2014), we find that our effort (messages) and engagement variables (comments, likes, and shares) are increasing over time.

Table 7 provides descriptive statistics for our time-series sample of 3,009 firm-year observations. Here we find that organizations send an average of 216 messages a year via their Facebook page. In terms of audience countersignaling, we find an average of 3,220 comments, 125,774 likes, and 19,731 shares. Overall, sample data suggests active signaling and countersignaling via Facebook in our sample.

[16] Because our time series sample of 3,009 firm-years includes organizations with and without a Facebook presence, we confirm the robustness of all results using this sample (Tables 9, 10 and 11) to excluding firm-years without a Facebook presence, as discussed in our additional analyses.

Table 7 Time-series sample descriptive statistics: firm-year observations

N = 3009	Mean	Med	SD	Q1	Q3
Messages_t	216	144	294	0	317
Comments_t	3,220	119	36,980	0	920
Likes_t	125,774	1,232	1,915,731	0	16,099
Shares_t	19,731	66	273,792	0	1,857
Donations_t	102,948,635	17,460,656	253,089,662	1,688,000	94,116,988
$\text{Fundraising Expenses}_{t-1}$	8,000,871	2,479,000	17,428,164	0	8,001,851
Age_t	50.99	48	40.96	23	69
$\text{Program Ratio}_{t-1}$	0.88	0.89	0.08	0.84	0.93
$\text{Total Assets}_{t-1}$	1,497,950,000	517,252,832	4,002,270,000	228,000,000	1,274,806,528
Gov Grants_{t-1}	85,104,944	2,456,872	275,260,274	0	39,483,252
Program Service Revenues_{t-1}	368,111,352	191,987,616	574,980,339	58,700,000	377,846,624

We present unlogged variables for ease of interpretation, but all continuous variables are logged in the multivariate tests

See Table 12 in the Appendix for variable definitions

Organization-specific financial characteristics presented in Table 7 are comparable to statistics presented in Table 3 for our cross-sectional sample of 427 unique organizations.

Using the time-series data summarized in Table 6, we first conduct two additional analyses to test the robustness of our Table 5 (H1) results. First, using this expanded time-series sample, we test the robustness of our findings to the *Facebook* presence test variable. As displayed in column (I) of Table 8, our results once again support Hypothesis 1 that Facebook presence is positively associated with aggregate donations. Our second analysis replaces the *Facebook* test variable with *New Facebook*, a binary variable indicating the first year the organization used Facebook as a communication channel. Results for this analysis are presented in column (II) of Table 8. Here we find that the first year an organization is on Facebook is associated with 18% higher level of contributions, compared to earlier and later years. These results lend further support to Hypothesis 1 and our proposition that establishing a social media presence is positively associated with donations.

4.2 Tests of signaling effort and audience engagement (H2 and H3)

Table 9 presents results for our second and third hypotheses using our expanded time-series sample (N = 3,009) of Facebook data from 2009 to 2016. Column 1 of Table 9 presents results for Hypothesis 2—that the amount of donations received will relate positively to organizational effort, as reflected in the number of Facebook messages sent. We find a positive and strongly significant coefficient on our test variable *Messages*, supporting our hypothesis that signals sent via social media are

Table 8 Hypothesis 1 robustness: time-series tests of existing and new social media presence

Dependent variable: $Donations_t$	(I) Coefficient *p-value*	(II) Coefficient *p-value*
Constant	−7.549***	−4.333***
	0.000	*0.000*
$Facebook_t$	**0.295*** **	
	0.000	
New $Facebook_t$		**0.165***
		0.073
Fundraising $Expenses_{t-1}$	0.215***	0.218***
	0.000	*0.000*
Age_t	−0.046	−0.039
	0.180	*0.298*
Program $Ratio_{t-1}$	3.321***	3.462***
	0.000	*0.000*
Total $Assets_{t-1}$	0.723***	0.701***
	0.000	*0.000*
Gov $Grants_{t-1}$	−0.010**	−0.010**
	0.013	*0.022*
Program Service $Revenues_{t-1}$	−0.071***	−0.075***
	0.000	*0.000*
Industry, Year & State Fixed Effects	YES	YES
N	3,009	3,009
Adjusted R^2	0.3420	0.3410

See Table 12 in the Appendix for variable definitions

*Significant at 10% level, **significant at 5% level, ***significant at 1% level (one-tailed for the bolded test variables, two-tailed for control variables)

associated with an increase in donations. Specifically, a 10% increase in messages is associated with a 0.7% higher level of donations.

The remaining columns of Table 9, in turn, report results of Hypothesis 3, which predicted the amount of donations received will be positively associated with countersignaling engagement. We find a positive and strongly significant association between donations and all three measures of countersignaling (*Comments*, *Likes*, and *Shares*). Economic significance is similar for each of the measures, with a 10% increase in the measure (*Comments*, *Likes*, and *Shares)* associated with a 0.7%, 0.5%, and 0.8% higher level of donations, respectively.

Given that the number of countersignals received by an organization depends on the number of messages initiated by the organization, we also scale our countersignaling measures by the number of messages received in columns III, V, and VII for *Comments*, *Likes*, and *Shares*, respectively. Here we again find positive

Table 9 Tests of hypotheses 2 and 3: signaling effort and audience engagement

Dependent Variable: $Donations_t$	Org. Effort	Audience Engagement					
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	$Messages_t$	$Comments_t$		$Likes_t$		$Shares_t$	
	Coef. *p-value*	Coef. *p-value*	Coef. *p-value*	Coef. *p-value*	Coef. *p-value*	Coef. *p-value*	Coef. *p-value*
Constant	− 7.437***	−4.638***	−6.876***	−7.402***	−7.097***	−7.131***	−6.845***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Test variable (column heading)	**0.067*** **	**0.069*** **		**0.053*** **		**0.078*** **	
	0.000	***0.000***		***0.000***		***0.000***	
Test variable/$messages_t$			**0.195*** **		**0.123*** **		**0.177*** **
			0.000		***0.000***		***0.000***
Fundraising $Exp._{t-1}$	0.213***	0.207***	0.205***	0.208***	0.204***	0.206***	0.204***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Age_t	−0.047	−0.057	−0.055	−0.054	−0.056	−0.048	−0.048
	0.176	*0.100*	*0.109*	*0.120*	*0.106*	*0.162*	*0.166*
Program $Ratio_{t-1}$	3.371***	3.447***	3.404***	3.408***	3.406***	3.429***	3.437***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Total $Assets_{t-1}$	0.717***	0.707***	0.691***	0.707***	0.692***	0.693***	0.683***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Gov $Grants_{t-1}$	−0.012***	−0.012***	−0.010**	−0.012***	−0.011***	−0.013***	−0.011***
	0.004	*0.002*	*0.018*	*0.004*	*0.005*	*0.000*	*0.000*
Program Service $Rev._{t-1}$	−0.071***	−0.071***	−0.069***	−0.071***	−0.069***	−0.071***	−0.069***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Industry, Year, State Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.3420	0.3452	0.3444	0.3453	0.3463	0.3460	0.3463

See Table 12 in the Appendix for variable definitions, all the values there are N=3,009

*Significant at 10% level, **significant at 5% level, ***significant at 1% level (one-tailed for the bolded test variables, two-tailed for control variables) associations between audience countersignaling and donations consistent with Hypothesis 3.[17]

Control variables in Table 9 are nearly identical to those in Tables 5: we see significant positive relationships with fundraising expenses, the program ratio, and size, and negative associations with government grants and program service revenues. Overall, the time-series tests shown in Tables 9 support H2 and H3 that donations are increasing with greater levels of organizational effort (*Messages*) and audience engagement (*Likes*, *Comments*, and *Shares*).

4.3 Tests of interactions with the donations demand model (H4–H6)

Our final three hypotheses are concerned with whether and how social media presence, effort, and engagement interact with the donations demand model. For these tests, we concentrate on the time series data, which allow year-to-year variation in organizational signaling conditions to test the robustness of the three core donations demand model variables—fundraising expenditures, age, and efficiency—interacted with social media. Table 10 presents results for these tests. Across all models, we find a strong substitution effect between our social media signaling variables and *Fundraising Expenditures*, supporting Hypothesis 4. These results are consistent with the notion that social media plays a fundraising communication role, potentially allowing organizations to pull back on traditional fundraising expenditures when they use social media platforms to connect with donors.

Interestingly, contrary to our expectations in Hypotheses 5 and 6, we find no significant interactive effect between our test variables and age or efficiency (*Program Ratio*), except when the test variable is measured as organizational presence on Facebook (column I). In this case, there do appear to be substitution effects, with older organizations and organizations reporting greater efficiency being associated with a reduced donation yield from having a social media presence, relative to younger and less efficient organizations. Differently put, while Facebook presence has an overall positive association with the dependent variable *Donations,* the association becomes weaker the older and more efficient the organization is.

4.4 Additional analyses and robustness tests

To further explore our hypotheses and examine the sensitivity of our findings to alternative specifications, we conduct a number of additional analyses and tests of robustness. First, organizations in some industries rely more on donations while others (such as health-related nonprofits and universities) may rely more on fees-for-services. While our main analyses include industry dummies to control for these differences in donor reliance and donor solicitation practices, we also conducted additional analyses that explicitly capture these differences. To test the differential impact of social media on donations at organizations classified as running more service-oriented businesses, we interact our social media test variables with an indicator variable activated for

[17] Our countersignaling models are also robust to including *Messages* as an additional control variable.

Table 10 Donation demand model interactions

Dependent Variable: *Donations*$_t$	Org. presence	Org. effort	Audience engagement		
	(I)	(II)	(III)	(IV)	(V)
	Facebook$_t$	Messages$_t$	Comments$_t$	Likes$_t$	Shares$_t$
	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*
Constant	−3.212***	−3.067***	−7.200***	−3.115***	−2.300***
	0.000	*0.001*	*0.000*	*0.000*	*0.008*
Test variable (defined in column heading)	**2.332*****	**0.340*****	**0.369*****	**0.255*****	**0.240*****
	0.000	***0.003***	***0.000***	***0.001***	***0.006***
Test variable* Fundraising Exps$_t$	**−0.054*****	**−0.017*****	**−0.019*****	**−0.013*****	**−0.013*****
	0.000	***0.000***	***0.000***	***0.000***	***0.000***
Test variable* Age$_t$	**−0.112***	**0.007**	**−0.013**	**−0.007**	**−0.002**
	0.043	***0.288***	***0.121***	***0.174***	***0.430***
Test variable* Program Ratio$_t$	**−1.112****	**−0.028**	**0.032**	**−0.010**	**0.037**
	0.051	***0.413***	***0.378***	***0.450***	***0.355***
Fundraising Expenses$_{t-1}$	0.238***	0.251***	0.255***	0.253***	0.236***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Age$_t$	0.066	0.012	−0.009	−0.001	−0.028
	0.210	*0.814*	*0.860*	*0.994*	*0.986*
Program Ratio$_{t-1}$	3.660***	3.271***	3.178***	3.209***	3.056***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Total Assets$_{t-1}$	0.771***	0.767***	0.757***	0.754***	0.736***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Gov Grants$_{t-1}$	−0.012***	−0.014***	−0.016***	−0.015***	−0.014***
	0.006	*0.000*	*0.000*	*0.002*	*0.002*
Program Service Revenues$_{t-1}$	−0.069***	−0.065***	−0.059***	−0.061***	−0.061***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Industry, Year, State Fixed Effects	YES	YES	YES	YES	YES
N	3,009	3,009	3,009	3,009	3,009
Adjusted R^2	0.3437	0.3464	0.3497	0.3480	0.3445

See Table 12 in the Appendix for variable definitions

*Significant at 10% level, **significant at 5% level, ***significant at 1% level (one-tailed for the bolded test variables, two-tailed for control variables)

service-oriented enterprises. Following Balsam and Harris (2014), we define *Service-Oriented* equal to one for organizations with a ratio of program service revenues to total revenues exceeding the sample median (78 percent). Organizations identified as service-oriented rely less on donations to fund their programs and may therefore have a unique relationship with social media.

Results for our test variables moderated by *Service-Oriented* are presented in Table 11. Consistent with our expectations, organizations that are service-oriented are associated with significantly less donations, as indicated by the significant negative

Table 11 Service-oriented versus donations-focused organizations

Dependent Variable: *Donations*$_t$	Org. Presence	Org. Effort	Audience Engagement		
	(I)	(II)	(III)	(IV)	(V)
	Facebook$_t$	*Messages*$_t$	*Comments*$_t$	*Likes*$_t$	*Shares*$_t$
	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*	Coefficient *p-value*
Constant	−5.920***	−5.861***	−5.857***	−5.892***	−5.558***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Test variable (defined in column heading)	**0.169*** **	**0.041*** **	**0.048*** **	**0.037*** **	**0.064*** **
	0.008	***0.002***	***0.000***	***0.000***	***0.006***
Test variable* Service-Oriented$_t$	**0.276*** **	**0.068*** **	**0.068*** **	**0.046*** **	**0.042*** **
	0.005	***0.000***	***0.000***	***0.000***	***0.001***
Service-Oriented$_t$	−1.153***	−1.229***	−1.275***	−1.249***	−1.141***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Fundraising Expenses$_{t-1}$	0.194***	0.191***	0.182***	0.185***	0.185***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Age$_t$	−0.036	−0.038	−0.052	−0.047	−0.041
	0.272	*0.245*	*0.115*	*0.151*	*0.210*
Program Ratio$_{t-1}$	3.205***	3.273***	3.359***	3.313***	3.330***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Total Assets$_{t-1}$	0.658***	0.652***	0.640***	0.641***	0.623***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Gov Grants$_{t-1}$	−0.020***	−0.022***	−0.023***	−0.023***	−0.024***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Program Service Revenues$_{t-1}$	−0.055***	−0.054***	−0.052***	−0.053***	−0.053***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
Industry, Year, State Fixed Effects	YES	YES	YES	YES	YES
N	3,009	3,009	3,009	3,009	3,009
Adjusted R^2	0.3616	0.3622	0.3654	0.3660	0.3663

See Table 12 in the Appendix for variable definitions

*Significant at 10% level, **significant at 5% level, ***significant at 1% level (one-tailed for the bolded test variables, two-tailed for control variables)

coefficient on *Service-Oriented*. In terms of our interacted variables, we find that across all five test variables, (*Facebook*, *Messages*, *Likes*, *Comments*, and *Shares*) *Service-Oriented* organizations using social media exhibit a stronger association with donations (significant positive coefficients on all interaction variables), relative to more donative organizations. We interpret this to mean that, while service-oriented organizations have a relatively low baseline level of donations, service-oriented nonprofits using social media communication channels are associated with larger increases in donations as a result of social media presence, effort, and engagement than their donative counterparts.

As a second extension of our main analyses, we partitioned our main results by the sophistication of the organizations' donor base. Following Yetman and Yetman (2013), we classify organizations reporting temporary or permanent restrictions on their net assets as those with more sophisticated donors. Untabulated results indicate that organizations with more sophisticated donors do not achieve a response to social media effort to the same degree that those with unsophisticated donors do. That is, the relationship between donations and social media effort is much stronger (*p-value* < 0.001) in our subsample of organizations without temporarily or permanently restricted net assets. We interpret this to mean that, rather than rely solely on information made available via social media, more sophisticated donors likely seek out and receive detailed inside information to evaluate the suitability of an organization for their large restricted donations. These findings point to a potentially interesting area for future research.

Finally, we test the robustness of our results to several model modifications. First, we re-ran our primary models with lagged independent test variables to determine whether social media presence, effort, and engagement were related to subsequent-year donations. The results substantively resembled those discussed above using contemporaneous test variables. We also confirmed the robustness of our results to excluding organizations that were never on Facebook, once again finding similar results. Similarly, we confirmed the robustness of our *New Facebook* test variable results to excluding organizations that were always on Facebook, finding consistent results. Lastly, we also confirmed the robustness of our models to excluding firm-year observations from 2016 (when only partial financial data was available in our time-series sample) as well as only including firms for which all eight years of financial data was available. Collectively, these tests of robustness lend greater credence to the fidelity of our results.

5 Conclusion

We have focused on the financial returns from three dimensions of an organization's social media activities. First, *whether* the organization has a social media presence. Second, *how much* the organization uses social media. Third, the level of *engagement* from the organization's audience. Employing a signaling theory framework, we posited that these social media activities attract donors by sending signals relevant to donors' impact-, status-, and relationship-related preferences. Our results are consistent with these ideas, suggesting that financial returns result from opening a new communication channel, from using that channel, and from having channel-specific audience engagement.

Beyond the practical relevance of these findings are the implications for the donations demand literature. Our first two hypotheses test channel selection and effort, while our third signaling dimension further extends the donations demand literature via an examination of audience countersignaling engagement. Countersignaling is relatively unexplored in the signaling literature, which is perhaps not surprising, given how costly it has generally been to obtain direct measures of stakeholder reactions to information. Fortunately, social media sites are distinct in how they allow for—and make publicly visible—both organizational signals as well as audience reactions and countersignals. In so doing, social media facilitates the examination of message effectiveness to a degree not readily available in other disclosure and reporting media.

We have also studied how social media signaling moderates key donations demand variables emphasized in the literature (e.g., Harris and Ruth 2015; Trussel and Parsons 2007; Yetman and Yetman 2013). Namely, we tested the interactions between social media signaling and the three variables at the heart of the predominant donations demand model: fundraising (fundraising expense), quality (age), and efficiency (program ratio). Here we find strong evidence that social media presence, effort, and engagement condition the functioning of the traditional donations demand model. Specifically, we find that social media exhibits a substitution effect on fundraising expenditures, supporting our argument that both fundraising and social media serve fundamentally communicative roles. We also contended that communication on social media would amplify the effects of organizational traits and thus generate complementary effects with organizational quality and efficiency. While we did not find evidence of a complementary effect—and, in fact, found evidence of substitution effects in our social media presence model—it is plausible the insignificant results are a product of the largely indirect nature of our proxies for quality and efficiency.

Finally, we tested the differential impact of social media presence, effort, and engagement in service-oriented versus donations-oriented organizations. We find that service-oriented organizations, which rely less on donations to fund their programs, appear to accrue additional benefits from their social media use.

These contributions notwithstanding, this study has limitations. To start, although our study models control for size, our sample consists of organizations much larger than the average nonprofit, which can be expected to be more actively engaged in social media. Accordingly, our findings may not generalize to the broader population of nonprofits. In addition, over half of the observations come from universities and health organizations, further reducing generalizability. In addition, while we have conducted numerous robustness tests, we cannot rule out the possibility that an omitted correlated variable, such as the talent and ability of the organization staff, is driving the results. Additionally, we acknowledge that our analyses fall short of testing the direction of the relationship between social media and donations, and we can therefore not infer causality. Finally, we have also not analyzed the content of the messages the organizations are sending, instead focusing on volume. Future research could examine whether donors react differently to different types of message content.

In terms of audience reactions, while we measure the extent of reactions in the number of likes, comments, and shares and indirectly get at the (positive) quality of that engagement in the number of "likes," we did not attempt to directly measure the overall favorability of audience interactions with the organizations' social media signals. Future research could thus extend our findings by examining what role audience sentiment plays in mediating organizational effort and donations outcomes. Lastly, given that this study uses aggregated annual data, we cannot test which individual signals or countersignals have the most influence on donations; the micro foundations of giving behavior could provide a valuable area of future research.

Overall, we believe the findings from this study are important for nonprofit managers interested in understanding the benefits of expanding their communications with donors and stakeholders via social media. Given that social media communications are less costly than print, radio or television advertising, this can be an important aspect of fundraising efforts for organizations wishing to reach donors while minimizing fundraising expenses. More generally, the findings from this study support the assertion that nonprofit organizations should consider investment in their social media presence. At the same time, our study stresses the idea that it is not enough to merely *create* a social media account; instead, there are increasing payoffs from regularly sending messages to cultivate an engaged social media audience. Overall, this study documents the importance of not merely a social media presence but of an *active* presence.

Appendix

Table 12 Variable definitions

Social Media	= 1 for organizations using any of the following forms of social media: Facebook, Twitter, Instagram, YouTube, Pinterest, LinkedIn, or Google+; 0 otherwise
Facebook	= 1 for organizations using Facebook, 0 otherwise
Twitter	= 1 for organizations using Twitter, 0 otherwise
Other Social Media	= 1 for organizations using any of the following forms of social media: Instagram, YouTube, Pinterest, LinkedIn, or Google+; 0 otherwise
Total Social Media	0 – 7 for the number of social media platforms used by an organization
New Facebook	= 1 for first year organization uses Facebook, 0 otherwise
Messages	Log of Facebook messages, 0 for those not on Facebook
Comments	Log of Facebook comments, 0 for those not on Facebook
Likes	Log of Facebook likes, 0 for those not on Facebook
Shares	Log of Facebook shares, 0 for those not on Facebook
Donations	Log of donations from Form 990
Fundraising Expenses	Log of fundraising expenses from Form 990
Age	Log of number of years since IRS ruling
Program Ratio	Program service expenses/Total expenses from Form 990
Total Assets	Log of total assets from Form 990
Gov Grants	Log of government grants from Form 990
Program Service Revenues	Log of program service revenues from Form 990
Service-Oriented	= 1 for organizations with the ratio of program service revenues to total revenues exceeding the sample median (78 percent), 0 otherwise

Acknowledgements We thank Steve Balsam, Chao Guo, and workshop participants at Drexel University, York University, and Rutgers University for helpful comments. Villanova School of Business MBA fellows provided research assistance.

Data availability Data are available from the public sources cited in the text.

Code availability Code used in this study is available upon request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Aiken, K.D., and D.M. Boush. (2006). Trustmarks, objective-source ratings, and implied investments in advertising: Investigating online trust and the context-specific nature of internet signals. *Journal of the Academy of Marketing Science* 34 (3): 308–323.
Amblee, N., and T. Bui. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce* 16 (2): 91–114.
Balsam, S., and E.E. Harris. (2014). The impact of CEO compensation on nonprofit donations. *The Accounting Review* 89 (2): 425–450.
Balsam, S., and E.E. Harris. (2018). Nonprofit executive incentive pay. *Review of Accounting Studies* 23 (4): 1665–1714.
Bartov, E., L. Faurel, and P.S. Mohanram. (2018). Can Twitter help predict firm-level earnings and stock returns? *The Accounting Review* 93 (3): 25–57.
Basoglu, K.A., and T.J. Hess. (2014). Online business reporting: A signaling theory perspective. *Journal of Information Systems* 28 (2): 67–101.
Bénabou, R., and J. Tirole. (2006). Incentives and prosocial behavior. *American Economic Review* 96 (5): 1652–1678.
Blankespoor, E. (2018). Firm communication and investor response: A framework and discussion integrating social media. *Accounting, Organizations and Society* 68: 80–87.
Blankespoor, E., G.S. Miller, and H.D. White. (2014). The role of dissemination in market liquidity: Evidence from firms' use of Twitter. *The Accounting Review* 89 (1): 79–112.
Cade, N.L. (2018). Corporate social media: How two-way disclosure channels influence investors. *Accounting, Organizations and Society* 68: 63–79.
Campbell, J.L., M.D. DeAngelis, and J.R. Moon. (2019). Skin in the game: Personal stock holdings and investors' response to stock analysis on social media. *Review of Accounting Studies* 24 (3): 731–779.
Cheung, C.M.K., B.S. Xiao, and I.L.B. Liu. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems* 65: 50–58.
Connelly, B.L., S.T. Certo, R.D. Ireland, and C.R. Reutzel. (2011). Signaling theory: A review and assessment. *Journal of Management* 37 (1): 39–67.
Croson, R., F. Handy, and J. Shang. (2009). Keeping up with the Joneses: The relationship between norms, social information and subsengequent charitable giving. *Nonprofit Management and Leadership* 19 (4): 467–489.
Curtis, A., V.J. Richardson, and R. Schmardebeck. (2016). Social media attention and the pricing of earnings news. In *Handbook of sentiment analysis in finance*, ed. G. Mitra and X. Yu, 212–232. New York: Albury Books.
Debreceny, R., G.L. Gray, and A. Rahman. (2002). The determinants of Internet financial reporting. *Journal of Accounting and Public Policy* 21 (4–5): 371–394.
Donath, J. (2007). Signals in social supernets. *Journal of Computer-Mediated Communication* 13 (1): 231–251.
Du, H., and W. Jiang. (2015). Do social media matter? Initial empirical evidence. *Journal of Information Systems* 29 (2): 51–70.
Elliott, W.B., F.D. Hodge, and L.M. Sedor. (2012). Using online video to announce a restatement: Influences on investment decisions and the mediating role of trust. *The Accounting Review* 87 (2): 513–535.
Elliott, W.B., S.M. Grant, and F.D. Hodge. (2018). Negative news and investor trust: The role of $Firm and #CEO Twitter use. *Journal of Accounting Research* 56 (5): 1483–1519.

Fischer, E., and A.R. Reuber. (2011). Social interaction via new social media: (How) can interactions on Twitter affect effectual thinking and behavior? *Journal of Business Venturing* 26 (1): 1–18.
Flannery, H., R. Harris, and C. Rhine. (2009). DonorCentrics Internet Giving Benchmarking Analysis. *Target* 1. https://www.issuelab.org/resources/28440/28440.pdf. Accessed 9 Aug 2019
Gallaugher, J., and S. Ransbotham. (2010). Social media and customer dialog management at Starbucks. *MIS Quarterly Executive* 9 (4): 197–212.
Glazer, A., and K.A. Konrad. (1996). A signaling explanation for charity. *American Economic Review* 86 (4): 1019–1028.
Gordon, T.P., C.L. Knock, and D.G. Neely. (2009). The role of rating agencies in the market for charitable contributions: An empirical test. *Journal of Accounting and Public Policy* 28 (6): 469–484.
Guo, C., and G.D. Saxton. (2014). Tweeting social change: How social media are changing nonprofit advocacy. *Nonprofit and Voluntary Sector Quarterly* 43 (1): 57–79.
Halvorsen, R., and R. Palmquist. (1980). The interpretation of dummy variables in semilogarithmic equations. *The American Economic Review* 70 (3): 474–475.
Harris, E.E., and D.G. Neely. (2016). Multiple information signals in the market for charitable donations. *Contemporary Accounting Research* 33 (3): 989–1012.
Harris, E.E., and D.G. Neely. (2021). Determinants and consequences of nonprofit transparency. *Journal of Accounting, Auditing & Finance* 36 (1): 195–220.
Harris, E.E., and J.A. Ruth. (2015). Analysis of the value of celebrity affiliation to nonprofit contributions. *Nonprofit and Voluntary Sector Quarterly* 44 (5): 945–967.
Hetze, K. (2016). Effects on the (CSR) reputation: CSR reporting discussed in the light of signalling and stakeholder perception theories. *Corporate Reputation Review* 19 (3): 281–296.
Hodge, F.D., J.J. Kennedy, and L.A. Maines. (2004). Does search-facilitating technology improve the transparency of financial reporting? *The Accounting Review* 79 (3): 687–703.
Hoffman, D.L., and M. Fodor. (2010). Can you measure the ROI of your social media marketing? *MIT Sloan Management Review* 52 (1): 41–49.
Jung, M.J., J.P. Naughton, A. Tahoun, and C. Wang. (2018). Do firms strategically disseminate? Evidence from corporate use of social media. *The Accounting Review* 93 (4): 225–252.
Krishnan, J., and P.C. Schauer. (2000). The differentiation of quality among auditors: Evidence from the not-for-profit sector. *Auditing: A Journal of Practice & Theory* 19 (2): 9–25.
Lasswell, H.D. (1948). The structure and function of communication in society. In *The communication of ideas*, vol. 37, ed. L. Bryson, 117–130. Urbana, IL: Univ. of Illinois Press.
Lee, L.F., A.P. Hutton, and S. Shu. (2015). The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research* 53 (2): 367–404.
Mangena, M., J. Li, and V. Tauringana. (2014). Disentangling the effects of corporate disclosure on the cost of equity capital. *Journal of Accounting, Auditing & Finance* 31 (1): 3–27.
McKeever, B. (2018). *The nonprofit sector in brief 2018.* Washington, DC: Urban Institute. https://nccs.urban.org/publication/nonprofit-sector-brief-2018. Accessed 8 July 2019.
Mollick, E., and R. Nanda. (2015). Wisdom or madness? Comparing crowds with expert evaluation in funding the arts. *Management Science* 62 (6): 1533–1553.
Mumi, A., M. Obal, and Y. Yang. (2019). Investigating social media as a firm's signaling strategy through an IPO. *Small Business Economics* 53 (3): 631–645.
Nelson, N. (2019). Tapping key takeaways from recent research on Fortune 500 social media usage. *Top Rank Marketing*. https://bit.ly/3o0PRDg. Accessed 21 June 2019.
Petrovits, C., C. Shakespeare, and A. Shih. (2011). The causes and consequences of internal control problems in nonprofit organizations. *The Accounting Review* 86 (1): 325–357.
Richardson, A.J., and M. Welker. (2001). Social disclosure, financial disclosure and the cost of equity capital. *Accounting, Organizations and Society* 26 (7–8): 597–616.
Sargeant, A. (2003). Relationship fundraising: How to keep donors loyal. *Nonprofit Management and Leadership* 12 (2): 177–192.
Saxton, G.D., D.G. Neely, and C. Guo. (2014). Web disclosure and the market for charitable contributions. *Journal of Accounting and Public Policy* 33 (2): 127–144.
Saxton, G.D., and L. Wang. (2014). The social network effect: The determinants of giving through social media. *Nonprofit and Voluntary Sector Quarterly* 43 (5): 850–868.
Saxton, G.D., and R.D. Waters. (2014). What do stakeholders "like" on Facebook? Examining public reactions to nonprofit organizations' informational, promotional, and community-building messages. *Journal of Public Relations Research* 26 (3): 280–299.
Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics* 87 (3): 355–374.

Statista. (2020). Most popular social networks worldwide as of July 2020, ranked by number of active users (in millions). https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/. Accessed 27 Oct 2020

Tinkelman, D. (1999). Factors affecting the relation between donations to not-for-profit organizations and an efficiency ratio. *Research in Government and Nonprofit Accounting* 10 (1): 135–161.

Tinkelman, D., and D.G. Neely. (2011). Some econometric issues in studying nonprofit revenue interactions using NCCS data. *Nonprofit and Voluntary Sector Quarterly* 40 (4): 751–761.

Trussel, J.M., and L.M. Parsons. (2007). Financial reporting factors affecting donations to charitable organizations. *Advances in Accounting* 23: 263–285.

Vaidya, M. (2014). Ice bucket challenge cash may help derisk ALS drug research. *Nature Medicine* 20 (10): 1080.

Wallace, E., I. Buil, and L. Chernatony. (2020). "Consuming good" on social media: What can conspicuous virtue signalling on Facebook tell us about prosocial and unethical intentions? *Journal of Business Ethics* 162 (3): 577–592.

Waters, R.D. (2011). Redefining stewardship: Examining how Fortune 100 organizations use stewardship with virtual stakeholders. *Public Relations Review* 37 (2): 129–136.

Weisbrod, B.A., and N.D. Dominguez. (1986). Demand for collective goods in private nonprofit markets: Can fundraising expenditures help overcome free-rider behavior? *Journal of Public Economics* 30 (1): 83–96.

Yetman, M.H., and R.J. Yetman. (2013). Do donors discount low-quality accounting information? *The Accounting Review* 88 (3): 1041–1067.

Yu, Y., W. Duan, and Q. Cao. (2013). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems* 55 (4): 919–926.

Zorn, T.E., S. Grant, and A. Henderson. (2013). Strengthening resource mobilization chains: Developing the social media competencies of community and voluntary organizations in New Zealand. *Voluntas International Journal of Voluntary and Nonprofit Organizations* 24 (3): 666–687.