Information and Donations:
A Study of Nonprofit Online Communication

by

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ABSTRACT

The question of how to increase individual donations is one of the biggest challenges facing nonprofit organizations. Although research shows that many factors can motivate individuals to donate, little is known about how nonprofits use information to actually increase donations. Using a mixed-methods design, this dissertation employs behavioral theories of charitable giving to explore: 1) the types of information communicated by nonprofit organizations to the public, and 2) how these communication efforts influence individual giving decisions.

As a first step in examining these issues, tweets communicated between the public and all nonprofits on the Topnonprofits.com 100 list were collected. The Topnonprofits.com 100 list ranks organizations by social media impact, website traffic, and Charity Navigator ratings. Big data analyses of these tweets show that there are four main types of communicated information: mission-related information, direct requests for donations, financial information, and performance-related information. The results also show that mission-related information and direct requests are more frequently communicated than the other two types of information. A cheap information model is then proposed to explain why mission-related information and direct requests are communicated more frequently.

Next, whether (and to what extent) the frequencies of each type of information about an organization are associated with public attitudes toward that organization is tested. Results of several multivariable regressions suggest there are no significant associations between frequencies of information communicated and public attitudes toward

nonprofits.

Finally, an online conjoint experiment is employed to explore the extent to which manipulation of the different types of informational messages (e.g., higher/lower evaluated missions, with/without direct requests, higher/lower program ratios, and higher/lower performance ratings) either boosts or decreases donations. These experimental results suggest that individuals are more likely to donate to a nonprofit that has a more highly evaluated mission, communicates direct requests, and has higher program ratios and performance ratings.

The results of this dissertation shed new light on the relationship between organizational information and individual donations. In addition to new theoretical insights, the findings from this dissertation should provide practical advice for nonprofit organizations on how to communicate information with donors more effectively.

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CHAPTER 1: INTRODUCTION

Donative financing of nonprofit organizations has long been considered critical to public goods provision, social service delivery, and democratic governance (Tocqueville 1840; Ostrom 1990; Putnam et al. 1994; Salamon 1999). Understandably, *"How to increase individual donations?"* has been one of the biggest questions facing many donative nonprofit organizations. This study refers to nonprofit organizations as those donative 501(c)3 public charities in which individual donations play a critical role in organizational revenues (IRS, 2008; NCCS, 2015). Payton and colleagues emphasized the importance of increasing individual donations by arguing that "fundraising is an essential part of American philanthropy; in turn, philanthropy as voluntary action for the public good is essential to American democracy" (Payton, Rosso, & Tempel, 1991, p. 4).

Donative income is a significant revenue source for many nonprofit organizations. At the sector wide level, among all the contributions to nonprofits in the United States (US), individual donations were the dominant contribution type from 1954 to 2014; followed by foundations, bequests, and corporations (Figure 1-1a). In 2014, Americans gave an estimated $358.38 billion to nonprofits. Among these contributions, $258.51 billion came from individual donations.

Individual donations have accounted for more than 70% of total contributions to the nonprofit sector for more than six decades (Figure 1-1b). In 2014, individual donations in the US increased 5.7% in current dollars over 2013 figures (GivingUSA, 2015). This persistent domination of individual donations, in many respects, demonstrates the significance and importance of donations to the nonprofit sector. Even though fees-for-services and goods are the main revenue sources for the nonprofit sector as a whole, individual donations are the main revenue source for donative nonprofit organizations (McKeever & Pettijohn, 2014; McKeever, 2015).

The fact that about 30% of individual donations went to religious organizations does not undermine the importance of studying individual giving to other 501(c)3 nonprofits—especially when considering that the growth rates of individual donations to nonprofits in the areas of art and culture (9.2%), environment and animals (7.0%), health (5.5%), public service (5.1%), education (4.9%), and human services (3.6%) were all larger than to religious nonprofits (2.5%) in 2014 dollars (GivingUSA, 2015; B. McKeever, 2015). To understand the rapid growth of individual donations to the above non-religious nonprofits, more studies on individuals' donative decision-making are needed.

Figure 1-1a: Overview of charitable giving in the United States 1954-2014 (amount in 2014 dollars)

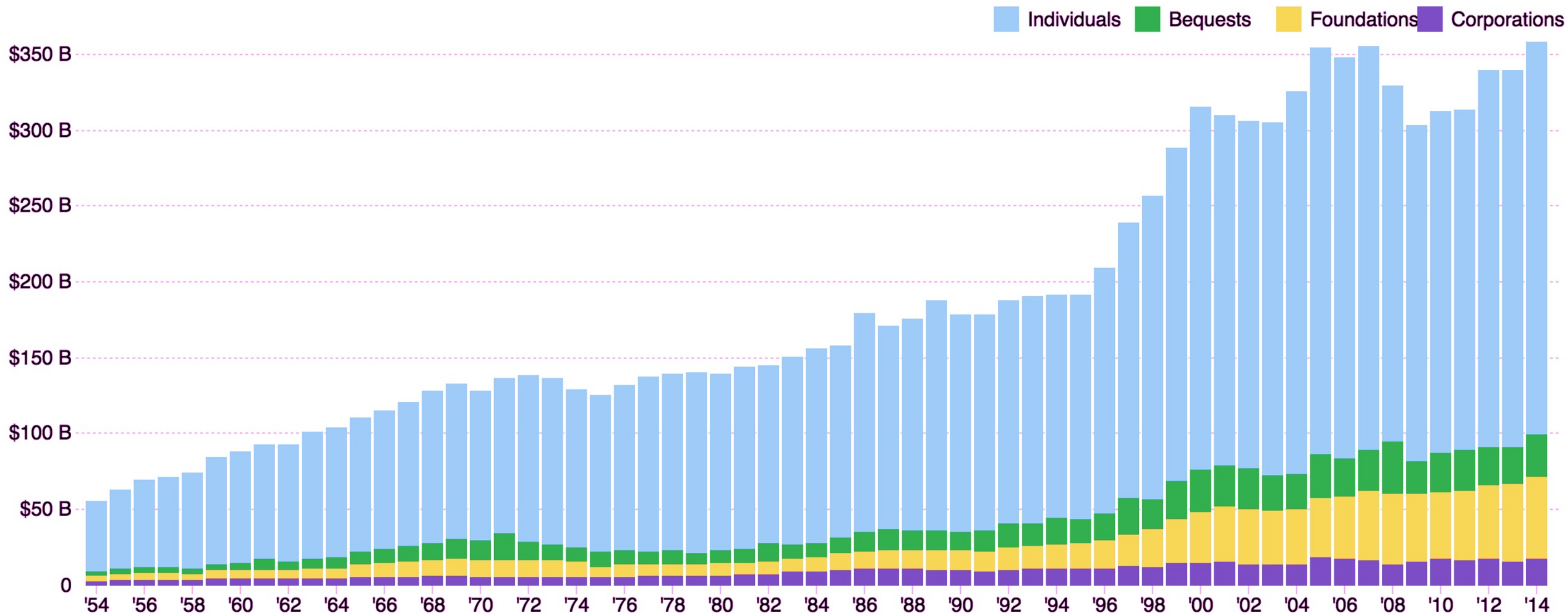
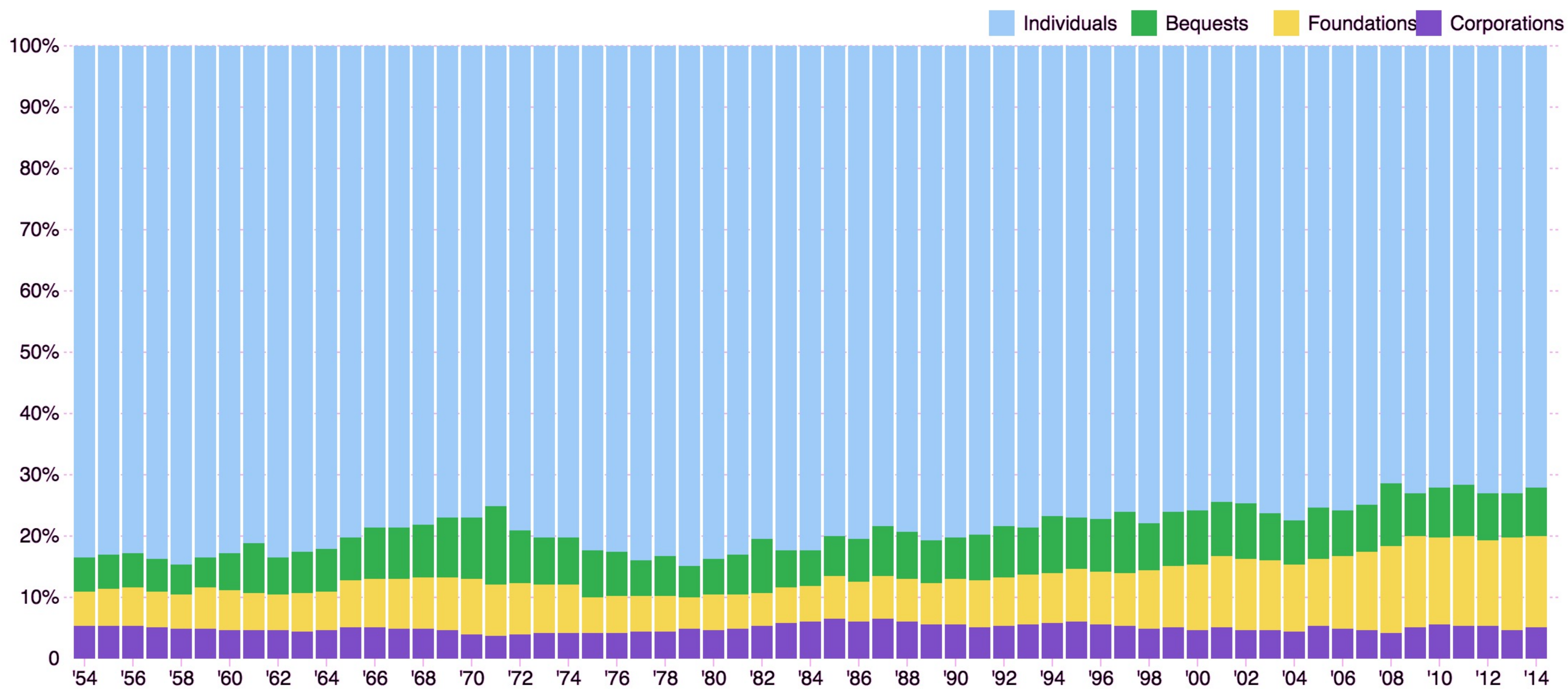


Figure 1-1b: Overview of charitable giving in the United States 1954-2014 (percentages of various donation sources)



Source: GivingUSA (2015) and Hall, Stiffman, Coddington, & Myers (2015).

Increasing amounts of donative income to nonprofit organizations is also considered a sign of good performance and accountability (Carnochan, Samples, Myers, & Austin, 2014; LeRoux & Wright, 2010; Stone & Cutcher-Gershenfeld, 2001; Weisbrod, 1989). Although it is difficult to measure the performance and accountability of a nonprofit, donations can signal the quality of the organization's performance and accountability (Bekkers & Wiepking, 2010; Glazer & Konrad, 1996; Karlan & List, 2007; List, 2011). Signaling theory suggests that a nonprofit must perform well and be accountable to be able to solicit more donations. If a nonprofit increases donations, these donations can be a sign of better organizational efficiency and accountability. In sum, studying individual donations to nonprofits is important not only because donations are the main revenue source for certain nonprofits, but also because donations are a measure of performance and accountability of these nonprofits.

However, information is asymmetric between nonprofits and donors. Information asymmetry negatively affects organizational efficiency and accountability by putting donors in an disadvantaged information position; and, thus, discourages donations (Hansmann, 1987; Steinberg, 2006; Young & Steinberg, 1995). Nonprofits have to communicate effectively with current and future donors to increase donations. For nonprofits, disclosure of information can be either mandatory, such as financial information required in filing the Internal Revenue Service (IRS) 990 Form; or voluntary, such as mission-related information and third party ratings that are not required by legal regulations. Both legal regulations and social pressures require nonprofits to communicate certain types of information to regulators, stakeholders, and the general public (Hall, 2010; Hopkins & Gross, 2010). In addition, to reduce informational barriers for donors (Buchheit & Parsons, 2006; Parsons, 2003, 2007; Saxton, Neely, & Guo, 2014), nonprofit organizations often try to strategically communicate customized information through proper channels with targeted donors.

Donors, having differing motivations, will likely require different types of nonprofit information to facilitate their giving decisions. To simplify, this study categorizes donors into two different types: *Type I* donors who are more self-centered and cause-driven, and *Type II* donors who are more altruistic and outcome-driven. Ideally, information asymmetry can be reduced if there is matched communication where Type I donors receive mission-related information (cause) and direct requests (being asked) and Type II donors receive financial and performance-related information (altruism and outcome). Mismatched communication between nonprofits and donors will result in ineffectiveness and is unlikely to elicit more donations to nonprofits (Parsons, 2007; Vesterlund, 2003). Thus, the question becomes: how can nonprofits customize information to meet targeted information needs?

In this digital era, most nonprofits will be unable to effectively communicate with donors without utilizing online tools, including organizational websites and social media. Although Li and McDougle (2017) found that online information channels have no significant influence on donors' giving decisions, their survey data for their study was collected in 2007 and did not specify social media as an information channel. During the past ten years, however, social media has grown exponentially. Therefore, this study focuses on Twitter communication between nonprofits and the public. Recent statistics indicate that 76% of US adults and 90% of nonprofits are using this particular social media platform (Lee, 2015; Pew Research Center, 2016), making it one of the most widely used forms of social media today.

Existing literature has investigated the impact of social media on various nonprofit goals. For example, nonprofits use Twitter for advocacy (Guo & Saxton, 2014), branding (Waters, Burnett, Lamm, & Lucas, 2009), and fundraising (Nonprofit Marketing Guide, 2017). Studies also explore how nonprofits utilize Twitter to engage stakeholders (Lovejoy & Saxton, 2012; Lovejoy, Waters, & Saxton, 2012) and find that nonprofits are more likely to use Twitter as a one-way communication tool, even though Twitter is designed for two-way communications.

Previous literature largely ignores the impact of information communication via social media on donations even though increasing donations is in fact a top goal of nonprofit communication (Nonprofit Marketing Guide, 2016, 2017). One study used data from Facebook to examine social media effects on donations and found that nonprofit efficiency ratios seemed to not have an impact and that fundraising success was related to nonprofits' web capacity, which was measured by the age and scope of the websites (Saxton & Wang, 2013).

However, the following questions remain unresolved:

(1) *What type(s) of information do nonprofits communicate to the public via Twitter?*

(2) *Are some types of information on Twitter communicated more than others? If so, why?*

(3) *What is the impact of nonprofits' Twitter communication on individual donations?*

(4) *Does different information content influence donors differently? If so, why?*

and, (5) *How can nonprofits communicate effectively with the public to increase donations?*

The purpose of this study is to provide preliminary answers to the above questions. The study tries to contribute theoretically by not only introducing new analytical methods such as big data analysis and conjoint experiment to nonprofit management studies, but also by providing new empirical evidence to advance our understanding of nonprofit communication strategies and donors' behavior. Instead of surveying nonprofit managers about what kind of information is used in communicating with the public, the study analyzes tweets between the two parties – nonprofits and donors – on Twitter to address the research gap of lacking actual empirical evidence of types of information communicated. The study also is intended to advance the understanding of donors' behavior by developing a cheap information model and using a conjoint experiment to investigate the impact of nonprofits' information on donors' giving decisions. The results could help nonprofits to develop more effective communication strategies that would increase donors' willingness to contribute.

The study then employs a mixed-methods approach to answer these questions. Figure 1-2 presents the conceptual framework of this study. The study first uses text-mining of big data (specifically, tweets) to explore the types of information communicated between nonprofits and the public. The findings from the study suggest that mission-related information, direct requests for donations, financial, and performance-related information are the four types of information most frequently tweeted. The study also finds that mission-related information and direct requests are communicated more frequently than the other information types. To explain why such a communication pattern exists, the study proposes a "cheap information" model, which suggests that nonprofits will customize "cheap information" to online audiences because nonprofits assume online audiences are more self-centered cause-driven Type I donors. The study further tests relationships between frequencies of the four types of information and public attitudes toward nonprofits. Results of these tests did not reveal any significant relationships. The insignificant results suggest that frequencies of cheap information do not impact public attitudes toward nonprofits; and, thus, has limited or no influence on donors' giving decisions since positive attitudes toward nonprofits predict increases in donations.

Finally, the study employs a conjoint experiment to investigate the impact of different types of information content on donors' giving decisions. Results from the conjoint experiment show that donors respond more favorably to:

- more highly evaluated nonprofit missions if missions belong to a same NTEE category (e.g. health nonprofits);
- simple requests such as "please help" and "thank you" than no request;
- higher program ratios of nonprofits than lower ones; and
- higher performance ratings (4 Charity Navigator stars) of nonprofits than lower performance ratings (3 Charity Navigator stars).

By answering the above questions, this study helps better understand nonprofit communication and individual giving decisions and, thus, may be able to help nonprofits develop more effective communication strategies. The remainder of this dissertation is structured as follows: Chapter 2 reviews the relevant literature. Chapter 3 presents the study of big data analyses of tweets communicated between nonprofits and individuals.

This chapter also includes the development of a cheap information model to explain nonprofit communication patterns. Finally, this chapter provides multivariable regression results of relationships between information frequencies and public attitude toward nonprofits. Chapter 4 uses a conjoint experiment to further investigate the effects of various contents of different types of information on individuals' giving decisions. Chapter 5 concludes and discusses both theoretical and practical implications of the study.

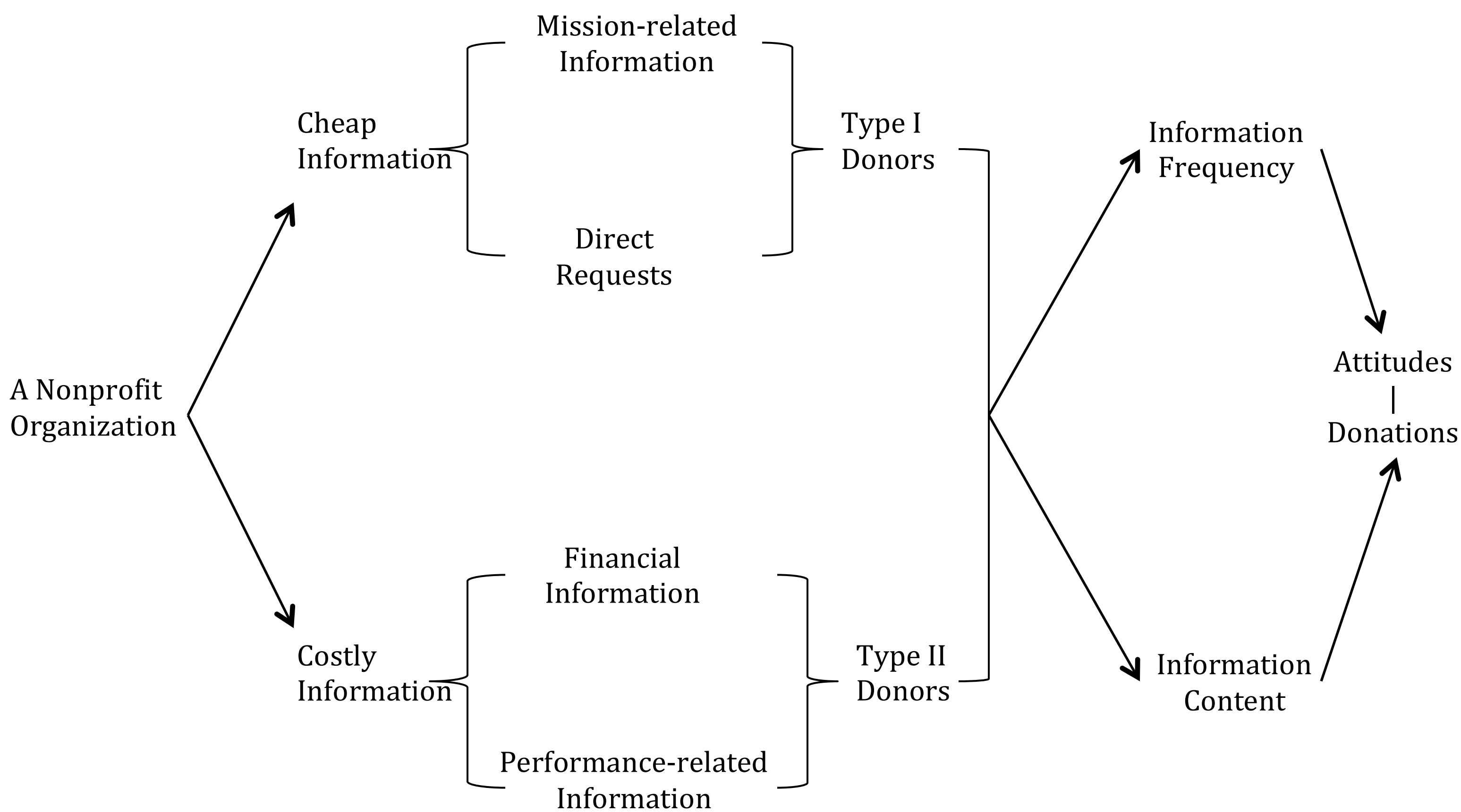


Figure 1-2：Conceptual framework

CHAPTER 2: LITERATURE: INFORMATION AND DONATION

2.1 Individual Donations

Nonprofit organizations are pivotal to a democracy. American democracy relies on not only the separation of governmental powers, but also a strong and viable civil society where nonprofit organizations play a vital role (Tocqueville 1840; Ostrom 1990; Putnam et al. 1994; Salamon 1999). Nonprofits fill in the niche market where the importance of social needs is not significant enough to mobilize government subsides and not profitable for private businesses (Hansmann, 1980, 1987; Young & Steinberg, 1995). Nonprofits thus provide public goods and services to satisfy such social needs. However, nonprofits cannot improve public goods provision without bearing costs. To survive and develop sustainably, nonprofits have to generate sufficient revenues (Kerlin & Pollak, 2010). Not surprisingly, then, "how to increase individual donations" becomes one of the biggest challenges facing many donative nonprofits.

Individual donations are important to donative nonprofits because donations constitute a large part of these nonprofits' total revenues. There is a consistent domination of individual donations over other sources of voluntary contributions to the nonprofit sector in the US. This domination of individual donations has lasted for six decades (GivingUSA, 2015; Hall et al., 2015). Since 1968, growth rates in donations roughly doubled the growth of the Standard and Poor's 500 (List, 2011). In 2014, 72% of total contributions to nonprofits were from individual donations; an increase of 13.88 billion dollars in individual giving was also the single largest factor associated with the increase in total contributions, accounting for 58% of the total change between 2013 and 2014 (GivingUSA, 2015). Individual donations are also the dominant mode of financial support for many of the largest nonprofits in the US, like the American Red Cross and the United Way (Rooney, 2006).

Studying individual donations has theoretical importance, besides its practical significance. The phenomena of individual donations motivates behavioral economists to challenge the rational choice theory proposed by traditional economics (Andreoni, 2008; List, 2011). Rational choice economics largely ignored pro-social behaviors including altruism and charitable giving for a long time. Becker was one of the few pioneer economists who brought “altruism” back to economic analyses (Becker, 1976, 1978). Other scholars then dug deeper into studying “altruism” to better our understanding of donations (for example, see Andreoni, 1989, 1990, 1998, 2008; Dellavigna, List, & Malmendier, 2012; Gneezy & List, 2006; Karlan & List, 2007). For instance, Andreoni (1989, 1990) argued that there was a “warm-glow” effect, which prevents governmental funds from totally crowding out individual donations. Experimental evidence has supported the warm-glow theory (Crumpler & Grossman, 2008; Dellavigna et al., 2012; Konow, 2010), which implies that charitable giving not only satisfies donors’ altruistic needs but also their self-interested needs (warm-glow effects). Studies of individual donations, thus, have contributed greatly to the development of behavioral economics.

Additionally, studying individual donations helps advance our understanding of human nature. Altruism is rooted in psychology and the neural foundations of human nature (Harbaugh, Mayr, & Burghart, 2007; Mayr, Harbaugh, & Tankersley, 2009; H. A. Simon, 1990; Tankersley, Stowe, & Huettel, 2007; Zak, Stanton, & Ahmadi, 2007). As Simon (1990) suggested, human docility and bounded rationality contributed to the evolutionary success of altruistic behavior. The studies of altruism and generosity go deeper and find that altruism is associated with neural responses (Mayr et al., 2009; Tankersley et al., 2007) and oxytocin (Zak et al., 2007). Ultimately, then, both theoretical and practical reasons urge us to advance our understanding of what individual donations mean to human nature and how nonprofits can more effectively increase donations.

2.2 Information Asymmetry

Efforts to increase donations are necessary for the health of nonprofit organizations. However, the information asymmetry that exists between nonprofits and donors is an obstacle for successfully soliciting individual donations. Information asymmetry occurs when one party has an information advantage over the other party or in a "principal-agent" relationship (Akerlof, 1970; Moe, 1984). In nonprofit settings, donors (the principal) contribute money to nonprofits (the agent). For example, nonprofits tend to have an information advantage of knowing when and where donations have been used. If donations are unrestricted, it is almost impossible for donors to monitor whether their money goes to programs or overhead expenses. Even though donors can monitor how nonprofits use their money, the costs will be high (McDougle & Handy, 2014; Steinberg, 2010). As such, nonprofits often disclose certain types of information in order to satisfy various needs from legal regulations, peer pressure (competitors), nonprofit watchdogs, public media, and stakeholders (Ebrahim, 2010). The availability of such information partially reduces the level of information asymmetry between nonprofits and donors.

However, information asymmetry problems cannot be solved if there is mismatched communication between nonprofits and donors. For instance, communicating financial and performance information is more effective with pure altruistic donors because such information meets their particular information needs of deciding whether or not to reduce their donations. Mission-related information is less effective or not effective at all to altruistic donors because of the mismatch between information provisions and information needs. Mismatched communication between nonprofits and donors results in ineffectiveness and is unlikely to elicit more donations to nonprofits (Parsons, 2007; Vesterlund, 2003).

The information asymmetry problem remains unsolved since organizational information is usually distributed by nonprofits through various information channels, which are not equally used by donors (Li & McDougle, 2017; McDougle & Handy, 2014). Some altruistic donors may rely on social media sources to search and gather financial and performance-related information. However, such information needs may not be met because the lack of social media specialists working in nonprofits and high information costs result in very limited or even complete absence of financial and performance information on social media outlets. As such, a miscommunication occurs due to a mismatched information channel.

A related problem is donors' unawareness of and unwillingness to seek certain types of information. One survey asked respondents to "best guess" the amount of government money received by nonprofits they supported and found no strong evidence that donors had accurate knowledge about government funding. Furthermore, when respondents were asked whether or not to change their giving due to an increase of government funding, 82% of them indicated that they would maintain the same donation level (Horne, Johnson, & Van Slyke, 2005). Donors' unawareness of financial information and unwillingness or inability to utilize such information can be potentially evident that donors are not motivated by financial information of nonprofits.

To fully solve the information asymmetry problem and thus increase donations to them, nonprofits have to communicate customized information with targeted donors through suitable information channels.

2.3 Donors' Motivations

Donors with various motivations respond differently to the same pieces of information about nonprofits. To effectively communicate information with donors and motivate them to contribute, nonprofits need to understand their donors' giving motivations. Table 2-1 summarizes the differences among various donative motivations proposed by different scholars and presents the categories of motivations used in this dissertation.

Bekkers and Wiepking (2010) identify eight different mechanisms that motivate individuals to donate: (*a*) awareness of need; (*b*) solicitation; (*c*) costs and benefits; (*d*) altruism; (*e*) reputation; (*f*) psychological benefits; (*g*) values; and (*h*) efficacy. Generally speaking, donors' awareness of the degree of need for help positively associates with the likelihood of charitable giving; a higher solicitation frequency is associated with increased donations; when the "price" of giving lowers and benefits such as special access to exclusive nonprofit services increase, donations increase; other financial resources nonprofits gained will crowd out pure altruists' donations; public recognition usually boosts charitable giving; if donors can have more psychological benefits (e.g. warm glow), they are more likely to donate; endorsement of pro-social values generally associates with donations positively; and organizational effectiveness also has a positive impacts on individual donations (Bekkers & Wiepking, 2010). Their review so far is the most inclusive and extensive survey of the mechanisms that incentivize donors from various disciplines such as economics, social and biological psychology, neural science, and so on. They argue that the eight mechanisms are more informative than the previous literature in the related fields. In practice, however, these eight mechanisms often do not function independently. Bekkers and Wiepking also acknowledge that the relative influence of each mechanism and their mixed effects vary over time, place, organizations, and donors (Bekkers & Wiepking, 2010, 2011; Wiepking & Bekkers, 2012). The inseparability of the effects of many mechanisms on donations suggests that several mechanisms may drive the same motivation of donors.

An individual can also have multiple and complex giving motives simultaneously. According to Ariely and his colleagues (2009), intrinsic motivation is the main incentive for altruistic donors; extrinsic benefits, such as tax deduction, incentivize donors who want material rewards associated with their giving behaviors; and image motivation mobilizes donors who want to earn a good reputation. When making a donation, a donor can be simultaneously incentivized by multiple motivations, such as warm glow, altruism, and image motivations.

Based on whether they are more self-centered or altruistic and whether they are cause-driven or outcome-driven donors (Table 2-1), this study categorizes donors into cause-driven, self-centered (Type I) donors and outcome-driven, altruistic (Type II) donors. The categorization is based on the nonprofit management angle: matching information with motivation by communication. This nonprofit management approach is different from, however not contradictory to, the individual donors' approach adopted by Andreoni and many others. For instance, Rose-Ackerman (1996, p. 712) argues "donors value not only the benefits supplied by the organization, but also their own act of charity."

In addition, Bekkers & Wiepking (2010, p. 936) claim in a similar way that "an obvious reason why individuals may contribute money to charities is because they care about the organization's output, or the consequences of donations for beneficiaries." These arguments suggest that some donors care about their own giving behavior while others take outcomes of their donations into consideration. Thus, nonprofit organizations have to satisfy these two different types of information needs.

Table 2-1: Various Motivations of Donations

Bekkers & Wiepking (2010)					Ariely, Bracha, & Meier (2009)	Andreoni (1989, 1990)	This study	
	What?	Where?	Who?					
Motivation	Tangible /intangible /both	Within /outside /between	Actors	Targets	Motivation	Motivation	Motivation	Information
Solicitation	Both	Between	Beneficiaries & organizations	Donors	Intrinsic	Warm glow	Type I	Direct requests & mission-related information
Psychological costs/benefits	Intangible	Within	Donors	Donors				
Need	Both	All	Beneficiaries & organizations	Donors				
Values	Intangible	Within	Donors	Donors & beneficiaries				
Reputation	Intangible	Between	Alters	Donors	Image			
Costs/benefits	Tangible	Outside	Organizations	Donors	Extrinsic	Altruism	Type II	Finance & performance-related information
Efficacy	Intangible	Within	Organizations	Donors				
Altruism	Tangible	Outside	Donors & organizations	Beneficiaries				

2.4 Organizational Information

2.4.1 Information types

There is, unfortunately, no consensus on how to categorize information about nonprofit organizations into "types." Some categories are more broadly defined, while others are more detail-oriented (Table 2-2). Financial and non-financial information are commonly used by many studies (for example, Buchheit & Parsons, 2006; McDowell, Li, & Smith, 2013; Parsons, 2003, 2007; Parsons & Trussel, 2008; Saxton & Guo, 2011; Saxton, Neely, & Guo, 2014) with disagreement on which specific pieces of information should be categorized into financial or non-financial information (Table 2-2). Parsons and colleagues find that donors are not only interested in financial information but also non-financial information (Buchheit & Parsons, 2006; Parsons, 2003, 2007; Parsons & Trussel, 2008). Parsons and Trussel (2008) use factorial analysis and suggest that the "price of output, program ratios, and administrative cost ratios" should be put into the "*efficiency*" category; "equity, revenue concentration, and operating margin" should be "*stability*"; "fundraising expense and its ratios" should be "*information*" and "age and size of the organization, grant, program, and other revenues" should be "*reputation*".

Saxton, Neely, and Guo (2014) discuss the critical importance of the distinction between the financial and performance (or mission-related) information of nonprofits. The ultimate goal for a private company is to maximize profits – a financial indicator. In contrast, the ultimate goal for nonprofits is intangible, such as to achieve a social mission. Therefore, it is critical to realize that financial efficiency is only one means to a higher end (Saxton et al., 2014). Saxton and colleagues (2014) find that donors are significantly more likely to respond to financial information than performance-related (mission-related) information, though both types of information impact donations positively. According to Saxton and colleagues, financial information includes annual reports, audited financial statements, privacy policies, investment pool performance, investment policies and/or strategies, administrative costs, and IRS Form 990. Performance or mission-related information focuses on the mission of the organization, list of recent grant awards, dollar amounts of grants awarded, introduction of a community foundation, summaries of funded projects, program or grant impact, and grantee stories. The results show that donors donate more when more financial information is available; donors, however, do not give more when more performance or mission related information is available to them, after controlling the level of financial information disclosure (Saxton et al., 2014).

McDowell, Li, and Smith (2013) categorize information into financial and non-financial information slightly different from the information types used by Saxton, Neely, and Guo (2014). In the study of McDowell, Li, and Smith (2013), nonprofit organizations' goals, outcomes, programs and missions constitute non-financial information while the program expense ratios and fundraising expense ratios constitute financial information. McDowell, Li, and Smith (2013) find that donors are more likely to gather non-financial information and integrate such information into giving decisions rather than to obtain and use financial information. The difference between the categorization of the two types of information is partially responsible for the contradictory results between McDowell, Li, and Smith (2013) and Saxton, Neely, and Guo (2014).

Other studies present information types in more detailed ways by listing specific pieces of information (Hyndman, 1990, 1991). Hyndman finds that donors rank organizational goals, problems (social needs), administrative costs, output, and efficiency as top five types of information needs. Waters (2007) identifies that nonprofits use four types of information–mission, goals, requests for donations, and annual reports–on their websites to communicate with the public, maintain good public relations, and increase donations.

The above discussion of various sets of information types show the complexity and difficulty of categorizating specific pieces of information. This study uses categories different from the above mentioned ones and is largely based on the National Center for Charitable Statistics at Urban Institute (NCCS, 2015) and the IRS 990 form. According to the NCCS (2015), there are generally four large categories of information about nonprofit organizations: (1), basic organizational information, such as organization names, locations, and leadership structures, and so on; (2), mission-related information, such as organizational missions, and social causes related to organizational missions, goals, and tasks; (3), financial information, such as revenues, expenses, and information on balance sheets; (4), performance information, such as outcomes and ratings from nonprofit watchdogs. Besides the above four types, direct requests for donations can be counted as a fifth (5) category since it is theoretically possible without presenting any information but organizations' names. Of course, some sophisticated solicitation and fundraising strategies can combine multiple types of information to motivate donors (Dellavigna et al., 2012; Handy, 2000).

The new five categories are neither too detailed nor too simplified and suit the research purpose of this study better than the other categories mentioned above. The new five categories capture almost all the information types and allow certain degrees of flexibility for re-categorizing. For instance, program ratios (the other side of overhead ratios) can be either performance or financial information.

Table 2-2: Information types

<table>
<tr><th>Hyndman (1990, 1991)</th><th>Waters (2007)</th><th colspan="2">Parsons (2007), Parsons & Trussel (2008)</th><th colspan="2">McDowell, Li, & Smith (2013)</th><th colspan="2">Saxton, Neely, & Guo (2014)</th><th colspan="2">This study</th></tr>
<tr><td>Goals</td><td>Goals</td><td rowspan="5">Financial information</td><td rowspan="5">Overhead ratios, Program ratios, Fundraising expense ratios</td><td rowspan="5">Financial information</td><td rowspan="5">Program ratios, Fundraising expense ratios</td><td rowspan="5">Financial information</td><td rowspan="5">Annual report, Audited financial statement, Privacy policy, Investment pool performance, Investment policy, Administrative costs, IRS 990 Form</td><td rowspan="2">Basic information</td><td rowspan="2">Names, Locations, Leadership structures</td></tr>
<tr><td>Social needs</td><td rowspan="3">Mission</td></tr>
<tr><td>Objectives</td><td rowspan="3">Mission-related information</td><td rowspan="3">Missions, Needs, Goals, Tasks</td></tr>
<tr><td>Officers</td></tr>
<tr><td>Output</td><td>Fundraising</td></tr>
<tr><td>Efficiency</td><td rowspan="5">Annual report</td><td rowspan="5">Non-financial information</td><td rowspan="5">Direct requests, Basic information, Social needs</td><td rowspan="5">Non-financial information</td><td rowspan="5">Nonprofit goals, Outcomes, Programs, Missions</td><td rowspan="5">Performance – related information</td><td rowspan="5">Mission, List of recent grant awards, Amount of grants awarded, Introduction of community foundation, Summaries of</td><td rowspan="3">Financial information</td><td rowspan="3">Revenues, Expenses, Balance sheets</td></tr>
<tr><td>Administration costs</td></tr>
<tr><td>Simplified operating statement</td></tr>
<tr><td>Simplified balance sheet</td><td rowspan="2">Performance information</td><td rowspan="2">Outcomes, Ratings from watchdogs</td></tr>
<tr><td>Audited operating</td></tr>
</table>

2.4.2 Information matters

For nonprofit organizations, communicating the right type of information to the right donors will, ideally, produce higher levels of donations to the organization. Atan, Zainon, and Wah (2012) use a charity organization's reporting index to measure the overall quality of information disclosure of nonprofits and find that a higher index score is significantly associated with a higher level of total contributions. In this part, I survey the empirical studies about impacts of direct requests, mission-related, financial and performance-related information on donations and discuss their limitations. I exclude the discussion about the impacts of basic organizational information due to the fact that basic information is always available and cannot be manipulated during communication. Table 2-3 summarizes the indirect and direct impacts on donations of four types of information. I then present my research questions and hypotheses for further examination.

The power of "asking". The effectiveness of solicitation or fundraising strategies is evident. When seed money (Gneezy, Keenan, & Gneezy, 2014; List & Lucking-Reiley, 2002), refunds for donations (List & Lucking-Reiley, 2002), matching grants and challenging gifts (Eckel & Grossman, 2008; Rondeau & List, 2008), and lotteries (Lange, List, & Price, 2007) are provided during solicitation, they all have positive impacts on donations, though, impacts on donations of different strategies vary. Solicitation or fundraising can employ sophisticated and complex strategies as mentioned above. These commonly used strategies aim at changing the price of giving.

However, how we ask also matters, even without changing the price of giving. In direct mail appeals, a nonprofit can use various types of information to signal its trustworthiness, which can bring more donations to the organization (Handy, 2000).

Furthermore, by altering the rhetorical, visual, and linguistic expressions in the appeal letters, nonprofits can solicit more donations. In a field experiment, participants are asked to allocate a hypothetical $100 to paired nonprofits with variations of rhetorical (rational, credible, or effective), visual (presence or absence of bulleted lists), and linguistic (readability or complexity of exposition) dimensions. The results show that credible and highly readable letters produce the largest amount of donations (Goering, Connor, Nagelhout, & Steinberg, 2009).

In addition, simple communication like “asking for help” is powerful in increasing giving to charitable causes and people in need (Andreoni & Rao, 2011). One possible explanation is that people feel good – warm glow - when they are being asked. The warm glow can stem from being needed and respected by others. Andreoni and Rao (2011) use the dictator game in which the dictator can allocate a given endowment ($10) arbitrarily to test the power of “asking”. In their experimental settings, non-communication is the baseline, with altered treatments: only the dictator can speak, only the receiver can ask, and a two way communication can exist. They find that when only the dictator can speak, only 6% of the endowment is donated by the dictator to other party, which is significantly lower than the non-communication baseline of 15%. When the receiver can ask, at least 24% of the endowment is passed from the dictator to the receiver. Asking is indeed powerful. The most striking result is that 30% of the endowment is passed to receiver when a two way communication is allowed.

An alternative theory about “asking” is that a person may try to avoid being asked because being asked to offer help can put psychological burdens on the person. In a field experiment during the Salvation Army’s annual campaign, researchers find dramatic avoidance of the solicitors (Andreoni, Rao, & Trachtman, 2011). They find, however, that simply asking "please help" increases donations by 75%.

In sum, impacts of simple direct requests without much detail on donations are largely unexamined by scholars. Empricial results on impacts of direct requests for donations are mixed, because they can be either powerful or stressful to donors. The mixed results demand further investigation.

Mission-related information. Missions of nonprofits, if well designed, associate with better performance because missions provide guidelines for decision making and signal organizational legitimacy to stakeholders (Kirk & Nolan, 2010). The Internal Revenue Service also encourages 501(c)3 nonprofits to establish and review regularly the organization's mission (IRS, 2008): "A clearly articulated mission, adopted by the board of directors, serves to explain and popularize the charity's purpose and guide its work. It also addresses why the charity exists, what it hopes to accomplish, and what activities it will undertake, where, and for whom." In a laboratory experiment, participants find non-financial information (mission-related information) to be useful for making giving decisions (Parsons, 2007). Kirk and Nolan (2010) find that mission statements that identified more target client groups are associated with larger one-year increases in contributions.

The organizational missions also enhance nonprofit brand recognition (Hankinson, 2002), which further increases donations. The organizational brand gives a whole image of a nonprofit organization to donors who usually make giving decisions based on their perception (Sargeant & Woodliffe, 2007). Sargeant, Ford, and Hudson (2008) study whether charity brand personality traits impact donors' giving and find that only "voice" and “emotional engagement” among traits of “benevolence, service, tradition, conservatism, emotional engagement, voice, and progressive” are positively associated with charitable giving. Stebbins and Hartman (2013) further the study of relationships between brand traits and donors’ giving and find that emotional engagement, voice, and progressive have stronger relationships with charitable giving. Their results also show that not only big and long lasting nonprofit organizations’ brands influence donors’ contribution positively but also small and relatively new nonprofits have positive branding effects.

As mentioned above, studies also show that donors want to gather more mission-related information (see, for example, Hyndman, 1990, 1991; McDowell, Li, & Smith, 2013). Hyndman (1991) finds a “relevance gap” between the information wanted by donors and that provided by nonprofit organizations. According to Hyndman (1991), almost all organizations disclosed their officers and audited financial reports, but only 38% provided some indication of organizational goals, 19% revealed administrative costs, 29% showed their output, and less than 10% indicated programmatic needs, future objectives, budget details, simplified balance sheets, or evidence of efficiency. Yet donors wanted to know most was the organizational goal. McDowell, Li, and Smith (2013) discover that donors are more likely to gather mission-related information, such as organizational goals and programmatic needs. However, Saxton and colleagues (2014) find the opposite is true: donors are significantly more likely to respond to financial information over performance-related (mission-related) information. Saxton and colleagues (2014), however, conclude that both types of information impact donations positively.

Donors, generally, are more likely to collect and use mission-related information to facilitate their giving decisions. And mission-related information is positively associated with donations.

Financial information. In a series studies (Buchheit & Parsons, 2006; Parsons & Trussel, 2008; Trussel & Parsons, 2007), Parsons and colleagues find positive impacts of disclosing more financial information on donations. Buchheit and Parsons (2006) experimentally investigate the role of accounting information in increasing donations – specifically, the presence of information about service efforts and accomplishments. Their results show that accounting information combined with typical fundraising appeals significantly increases giving intentions, although not actual donations. Trussel and Parsons (2007) investigate how financial reporting factors influence donations and find significant positive impacts of administrative efficiency, financial stability, fundraising effectiveness, and program revenues and grants. Saxton and colleagues (2014) also find that financial information is more useful in motivating donors, as mentioned earlier.

Administrative efficiency is found to be positively associated with charitable donations (Tinkelman & Mankaney, 2007; Trussel & Parsons, 2007). Reducing overhead fees or the ratios of administrative costs will increase administrative efficiency and thus increase donors' contribution. Parsons and Trussel (2008) find that donors tend to donate to the charitable organizations, which have low operation costs. In a field experiment with 40,000 potential donors, Gneezy and colleagues (2014) find that informing donors that overhead fees are covered by an initial donation significantly increases the donation rate by 80% and total donations by 75% compared with using the initial donations as the seed money. Donors want their money to have a real impact and thus prefer their donations being spent on projects rather than on overhead or administration. The results of Gneezy and colleagues (2014) support the conclusion made by Tinkelman (1999) that efficiency ratios impact donations in a positive way.

The other critical financial indicator is government funds. The second-largest proportion of public charities' revenue came from fees from government contracts; these fees accounted for 24.5% of public charities' revenues in 2013. Government grants represented another 8%. When combining government contracts and grants into a single category, the government provided nearly one-third (32.5%) of 2013 nonprofit revenues (NCCS, 2015). Existing literature investigates the relationship between government funding and individual giving to charities (Andreoni, 2006; Brooks, 2000a, 2000b; Diamond, 1999; Kim & Van Ryzin, 2014; Nikolova, 2014; Steinberg, 1985) and identifies the crowding in (Brooks, 1999; Diamond, 1999) and crowding out effects (Andreoni & Payne, 2003, 2011a; Kim & Van Ryzin, 2014). Brooks (2000a) reviews 22 empirical studies of the effect of government funding to charities and finds mixed results: 13 of these studies support the crowding out effect, with 4 supporting crowding in and 5 finding no significant relationship between government funding and private giving. Meta analyses of empirical studies on crowding out effects also show mixed results (de Wit & Bekkers, 2016; Lu, 2016).

Many later studies show that governmental grants reduce fundraising efforts of nonprofits. For instance, Okten and Weisbrod (2000) find that nonprofits will stop devoting efforts to fundraising once governmental grants enable nonprofits to meet their revenue expectations. Andreoni and Payne (2003) find a significant correlation between governmental grants and a decrease in nonprofits' fundraising costs. Different estimations show that a $1,000 increase in governmental grants will decrease more than

10% of an organization's fundraising expenditures. Their later study also finds crowding out effects, which show that for each governmental dollar organizations received, there is a reduction of 14 cents in fundraising efforts (Andreoni & Payne, 2011b). The above studies, however, are focusing on organizational decisions of reducing fundraising efforts rather than on individual decisions of reducing donations.

In terms of individual giving, variations across different types of NPOs may contribute to the determination whether there is a crowding out or crowding in effect. When art related charities and science related NPOs are receiving government grants, there are crowding in effects (Diamond, 1999). Many empirical results find a nonlinear relationship between government funding and individual giving (Borgonovi 2006; Nikolova 2014; Steinberg 1985): at lower levels, government funding to charities attracts private contributions; however, at higher levels, government grants crowd out individual contributions to charities. A recent study also finds a curvilinear relationship between government grants and charitable giving to private voluntary organizations (PVOs). Public revenues attract additional private funds when government funding is no more than a third of all revenues of PVOs; but beyond that level, they discourage private giving (Nikolova, 2014). The previous studies of crowding in or crowding out are based on the assumption that donors act on the information of government funding to charities in making their giving decisions. Horne and colleagues (2005) challenge the crowding in/out theories by demonstrating that donors may be not aware of the government funding to their supported nonprofits when they make giving decisions. 45% of the respondents report that are uninformed about the "information" of government grants, and 82% of the respondents report that they will not change their donations with more information about governmental grants to their supported nonprofits.

In sum, disclosing more financial information about nonprofits helps increase donations. Various types of financial information, however, influence donations differently. Administrative efficiency (e.g. low overhead ratios) produces more donations; the impacts of government funds are unclear.

Performance information. Though there is no consensus about what should be categorized as performance information due to the difficulties of measuring the intangible nonprofit performance, scholars usually accept ratings or rankings from independent agencies or nonprofit watchdogs as a measure of nonprofit performance. The Better Business Bureau's Wise Giving Alliance, Guide Star, and Charity Navigator are widely recognized nonprofit watchdogs. Ratings or rankings from these watchdogs signal the aggregated information of nonprofit organizations' performance and accountability. However, very few donors use the rating information of nonprofits to facilitate making their giving decisions (Cnaan, Jones, Dickin, & Salomon, 2011; Gordon, Knock, & Neely, 2009). Cnaan and colleagues (2011) find that nearly seventy-eight (78) percent of donors do not consult results provided by nonprofit watchdogs to facilitate their giving decisions. They also find that low-income donors are more likely to rely on their social networks, such as "word-of-mouth" from families and friends, rather than ratings (Cnaan et al. 2011), even though the information costs associated with consulting rating agencies are much lower than other information sources (Sloan, 2009). Therefore, the usefulness of watchdogs' ratings is not unquestionable.

Table 2-3: Impacts of information on donations

Information types	Indirect impacts on donations	Impacts on donations	Literature
Direct requests		+	Andreoni et al., 2011; Andreoni & Rao, 2011; Das, Kerkhof, & Kuiper, 2008; Dellavigna et al., 2012
	- (avoid requests)		Andreoni et al., 2011
Mission-related	+ (administrative efficiency)	+	Kirk & Nolan, 2010
	+ (search for mission)		Hyndman, 1990, 1991; McDowell et al., 2013; Parsons, 2007
	+ (branding)		Hankinson, 2002
	+ (donation intentions)		Das et al., 2008
Financial		+	Buchheit & Parsons, 2006; Parsons & Trussel, 2008; Parsons, 2003, 2007; Saxton et al., 2014; Trussel & Parsons, 2007
		-	Gneezy et al., 2014
		+	Brooks, 1999; Diamond, 1999
		-	Andreoni & Payne, 2003, 2011a; Kim & Van Ryzin, 2014
Performance-related		+	Saxton et al., 2014; Sloan, 2009
	- (unlikely to use rating)		Cnaan, Jones, Dickin, & Salomon, 2011
	- (low disclosure score)		Atan, Zainon, & Wah, 2012

CHAPTER 3: BIG DATA, CHEAP INFORMATION

3.1 Introduction

By providing public goods and social services, nonprofit organizations play a critical role in the development of a robust civil society and the enhancement of democratic governance. Increasing donations can thus be considered as a lever to coproduce public goods and to enhance democracy, since donations are crucial to the sustainable development of nonprofit organizations (Payton et al., 1991). Individual donations, which have accounted for more than 70% of the total contributions to the nonprofit sector for more than six decades in the United States, are always pivotal revenue sources for donative nonprofit organizations (GivingUSA, 2015; McKeever, 2015).

To increase donations is always a challenge for nonprofits. Information asymmetry between organizations and donors is one of the main barriers to increasing donors' contributions to nonprofits. Effective communication can help reduce information asymmetry, enhance mutual trust, and increase donations to nonprofits. In 2016, about 73% nonprofit executive directors and 79% development directors placed "acquiring donors" as the priority goal of communication; and about 68% executive directors and 85% development directors considered "retaining donors" as one of the top ranked goals of communication (Nonprofit Marketing Guide, 2017). Therefore, in order to increase donations, nonprofits have to communicate effectively with potential and current donors.

Effective communication requires nonprofits to decide the informational channels to be used for communicating with donors, the types of information, and the amount and contents of each type of information. In this digital age, nonprofits cannot communicate with donors effectively without utilizing online tools, including organizational websites and social media, such as Facebook, Twitter, and YouTube (Nonprofit Marketing Guide, 2017). The 2016 Nonprofit Communications Trends Report asked more than 1,600 nonprofit professionals to rank four most important communication channels and found that the five most important communication channels are website (80%), social media (70%), email (67%), events (46%), and print (39%). The top three choices are all online communication channels.

Aside from the information channels, nonprofits also have to decide what kind of information to share with individuals, who have various information needs. The amounts and contents of organizational information also shape public attitudes toward nonprofits and thus influence giving decisions. A study of 400 nonprofit organizations in the United States found a positive relationship between the amount of charitable contributions and the level of information disclosure on organizational websites (Saxton, Neely, & Guo, 2014). More information disclosed online reduced the information asymmetry and made a nonprofit more transparent. The increased level of transparency helped earn donors' trust and donations. The contents of information, such as stories, statistical numbers, and framings, also influence donors' giving decisions (Kim, Mason, & Li, 2017; Small, Loewenstein, & Slovic, 2007).

Given the importance of online communication, very little is known about the types of information and the frequency and contents of each type of information that nonprofits communicate with the public. In addition, the impacts of such communication remain unclear. This study first analyzes big data of tweets to explore what types of information are communicated between nonprofits and the public and discovers four main information types: mission-related information, direct requests for donations, financial information, and performance-related information. The study then provides a preliminary answer to the question of why mission-related information and direct requests for donations are more frequently communicated on Twitter than financial and performance-related information. The study also finds there are no significant associations between frequencies of tweeted information and the public attitude toward nonprofits. The public attitude is often regarded as a strong predictor of donations.

The rest of this study is organized as follows: Section 3.2 provides a brief review of literature. Section 3.3 presents the procedures and results of big data analyses of tweets communicated between nonprofits and the public. Section 3.4 explains why mission-related information and requests are communicated more frequently than financial and performance-related information. Section 3.5 tests the associations between frequencies of various types of information and the public attitude toward nonprofits. Section 3.6 concludes and discusses the implications, limitations, and future plans.

3.2 Literature Review

3.2.1 Online communication channels

In this digital age, the importance of online communication is self-evident. Nonprofits have to acquire and retain donors through various information channels to increase donative revenues. However, in terms of attracting donations, roles of different information channels vary. For example, based on a survey of more than 1,000 residents in San Diego County, California, a recent study discovered that individuals who got organizational information from personal experience and nonprofit crediting agencies were more likely to give time to nonprofits; but relying on various informational sources had no significant impact on individuals' donation decisions (Li & McDougle, 2017). The San Diego County survey was conducted in 2007. During the last decade, information technology has developed dramatically. Online communication via websites, social medias, and emails is far more commonly used by nonprofits than traditional means such as direct mails and events (Nonprofit Marketing Guide, 2016, 2017).

The rapid growth of social media deserves special attention. For example, according to the Pew Research Center (Greenwood, Perrin, & Duggan, 2016), 24% of internet users use Twitter. This is a significant portion of all the adults in the U.S. (21% of all U.S. adults). However, Twitter users tend to be younger. 36% of online adults are between ages 18 to 29. Their share is more than triple the share of internet users who are age 65 and older (10%). Twitter users are also more educated (29% of them have college degrees) and wealthy (58% have an annual income more than 50,000 dollars). Therefore, conclusions drawn from the study cannot be generalized without careful deliberation.

On the other hand, close to 90% of nonprofit organizations have Twitter accounts (Lee, 2015). Nonprofits tweet for multiple purposes, such as advocacy (Guo & Saxton, 2014), branding (Waters et al., 2009), and fundraising (Nonprofit Marketing Guide, 2016, 2017). Studies also investigate how nonprofits format information on Twitter: tweet frequency, following behavior, hyperlinks, hashtags, public messages, retweets, and multimedia files (Lovejoy et al., 2012; Waters & Jamal, 2011). One interesting finding is that on Twitter where two-way communication is encouraged, nonprofit organizations are more likely to only tweet one-way (Waters & Jamal, 2011). Communication aimed at garnering contributions could be very difficult without utilizing popular social media, such as Facebook and Twitter. This study focuses on Twitter communication between nonprofits and the public.

3.2.2 Types, amounts, and contents of information

As discussed above, nonprofits have to understand influences of various types, amounts, and contents of organizational information before making effective communication strategies that can translate information into donations. Different types of information influence donors in different ways. Cause-driven donors are more likely to respond to mission-related information rather than financial and performance-related indicators. Even the same piece of information, such as the ratio of governmental funds to total organizational revenues, has competing impacts on donors: it could crowd in donations if donors view the governmental funds as a quality signal of the nonprofit, or crowd out donations if such governmental funds are considered as substitutions for individual donations (de Wit & Bekkers, 2016; Lu, 2016).

Moreover, should nonprofits communicate certain types of information more frequently than other types? Or should all types of information be communicated equally? For instance, Saxton and colleagues (2014) find that financial information is more attractive to donors than performance-related information. Under such a circumstance, it is unwise and inefficient for nonprofits to devote more resources into communicating performance-related information with the public. However, Saxton and colleagues (2014) do not mention that the effects of the financial information might vary across different donors with different giving motivations. Ideally, to design effective communication strategies, nonprofits should customize information for targeted donors.

Nonprofits should also consider how to present a certain piece of information during communication due to the fact that various forms of the same type of information could influence donors quite differently. Very few studies pay attention to the content of the information carried by these communications (for a detailed discussion, see Graber, 2003) and the impacts of such contents on various outcomes desired by nonprofits. In terms of increasing donations to a nonprofit, telling an emotional story related to an organization's mission is more useful than a plain mission statement (Merchant, Ford, & Sargeant, 2010); presenting a picture of rebuilding a place after earthquake is more powerful than describing the same event in text (Kim et al., 2017); providing information of identified clients is more useful than providing statistics of clients (Small et al., 2007); positively framing a piece of information is more useful than framing negatively (Andreoni, 1995); and simple direct requests for donations are more powerful than not asking (Andreoni & Rao, 2011).

3.2.3 Relationships between communication and donations

Ideally, effective communication can increase individual donations to nonprofits by making organizations more transparent, reducing information asymmetry, and enhancing mutual trust. However, very few studies examine the relationships between communication and donations. Saxton and Wang (2013) explore the determinants of giving to nonprofits through Facebook and find organizations' web capacities matter, rather than organizational efficiency. The effects on donations of communicating financial information differ from the effects of communicating performance information. According to Saxton and colleagues (2014), more financial information is positively associated with more donations to nonprofits. More performance-related information, however, does not have the same effect.

Studies have investigated the relationships between communication and nonprofit accountability. For example, Saxton, Guo, and Brown (2008) study 117 community foundations' websites and identify key dimensions of online nonprofit responsiveness. In a follow up study, authors use a four-factor model – organizational strategy, capacity, governance, and environment – to explain web-based online accountability (Saxton & Guo, 2011). Guo and Saxton (2014) study the role of Twitter in nonprofit advocacy. Other studies investigate how to engage stakeholders by using Facebook (Waters et al., 2009) and Twitter (Lovejoy et al., 2012). It should also be noted that communication could affect donations indirectly through influencing public attitudes toward nonprofits. Public attitude is a strong predictor of donations to nonprofits and other pro-social behavior (Eayrs & Ellis, 1990; Eisenberg & Miller, 1987; Webb, Green, & Brashear, 2000).

In sum, the solutions to the following questions remain unclear: what types of organizational information are communicated on Twitter between nonprofits and the public? Are certain types of information more frequently communicated than the others? If so, why? And is such communication associated with a more positive public attitude, which further predicts donations to nonprofits? Without a closer look at the contents of the communicated information, it is difficult for nonprofits to understand the real factors inside the informational messages that motivate donations, and thus it is also unlikely they will develop more effective strategies to increase future donations. This study first employs text-mining of big data to explore what types of information are communicated on Twitter; then presents a model based on game theory to explain why certain types of information are more frequently tweeted than the others; and finally, uses multivariable regressions to test the relationships between frequencies of certain types of communicated information and the public attitude toward nonprofits.

3.3 What Types of Information Are Communicated on Twitter?

3.3.1 Big data analyses of tweets

The study first employs a mixture of grounded theory and functionalism perspectives (Creswell, 2013) to explore what types of information are communicated on Twitter. The analysis is grounded in the contents and themes that emerge in tweets. At the same time, five categories of information – basic organizational information such as organizational names and locations, mission-related information including project information, direct requests for donations and fundraising messages, financial information, and performance-related information – are used to guide the exploration of the communicated tweets. Basic organizational information - such as location and year established - is excluded due to the fact that it is very rarely tweeted. Therefore, this study only focuses on the remaining four types of information.

The combination of two different qualitative perspectives – grounded theory and functionalism (Creswell, 2013, 2014) – suits this study. Grounded theory is particularly with small amounts of data because it allows researchers to observe emerging themes. In terms of the grounded perspective, previous studies usually interviewed nonprofit managers or donors to gain content data for analyses. For example, Hou and Lampe (2015) interviewed 26 social media professionals who work for small nonprofit organizations to learn how they use social media to support their organizations' public engagement. Very few studies actually analyzed contents from tweets (Lovejoy et al., 2012) or Facebook pages (Waters et al., 2009) to show how nonprofits can engage stakeholders through social media. Furthermore, neither Lovejoy et al. (2012) nor Waters et al. (2009) actually used big data analysis. Waters and Jamal (2011), who made an effort to analyze the content tweeted by nonprofits, did not include an analysis of the two-way communications between nonprofits and the public on Twitter.

In terms of text-mining of big data, content analyses would lack direction without certain guidance because of the inability of humans to analyze huge amounts of data. A widely used solution to analyzing big data is to employ a supervised machine learning program (Athey, 2017; Liu, 2015). However, any kind of machine learning at this stage is not reliable without "human supervision" (Grimmer & King, 2011). Therefore, this study uses four pre-determined types of information – mission-related information, direct requests, financial information, and performance-related information – to guide the exploration of tweets. The large categories of information used here differ from the categories employed by other scholars. For instance, Saxton and colleauges (2014) treated the IRS 990 Form as financial information. The IRS 990 Form actually contains other information, such as basic organizational information of a nonprofit and the National Taxonomy of Exempt Entities (NTEE) codes. In addition, government grants to nonprofit organizations are classified as financial information in this dissertation. Saxton and colleagues (2014) categorize such information about governmental grants as performance related information. Another example is the annual report, which was treated as an individual category in Waters (2007) but categorized into financial information by Saxton and colleagues (2014). In this dissertation, balance sheets in annual reports are listed as financial information; while project outcomes are treated as performance related information. In other words, annual reports contain both financial and performance related information. Regardless of the differences in categorization of information, it is useful to explore the types of information and the detail within a particular type used in actual communication. It helps answer questions such as "to what extent and why certain types of information are communicated between nonprofits and the public?"

In order to do so, the study first searched the keywords "donation" and "fundraising" across Twitter, which is one of the most frequently used social media around the world, to gain insights into the topics that were discussed when users included these terms in their tweets. A special R program was designed to download 500,000 tweets for each keyword from Twitter.com. These tweets were downloaded in five different waves in 2016: February 11, March 1, April 20, April 28, and May 16. For each wave, the R program requested and downloaded 100,000 tweets of each key word from Twitter.com through a specially developed application. Downloading tweets from various time periods helped avoid the influence of one big event of "donation" or "fundraising" that might bias the findings. For instance, in February 2016, the political fundraising campaigns launched by different presidential candidates dominated the communication and discussion about "fundraising" on Twitter. Thus, only using tweets from the February 2016 might present misguided results. The study then analyzed the downloaded tweets to figure out a general picture of the information that was being communicated when nonprofits, professionals, and the public were talking about "donation" and "fundraising".

The study clustered the most frequently communicated words and then categorized the clusters into different types of information. When hundreds of thousands of tweets are presented, it is practically difficult for human coders to review and evaluate all the tweets and then code them into categories. Computer-assisted clustering methods based on natural language process algorithm are thus useful to analyze big data. In order to further reduce the complexity and provide evidence of what was most frequently communicated about "donation" and "fundraising" on Twitter, ten clusters were set up, and only words that appeared with more than ninety-nine percent frequency were included. A special algorithm was programmed in R for clustering tweets about "donation" and "fundraising". The four information types mentioned above served as the coding criteria. The study first produced word clouds of "donation" and "fundraising". After that, it drew up a ten-diagram dendrogram of clusters with each of the most frequently appearing words on the left, and then nested hierarchically to the right. The method used for clustering here is a widely accepted approach, which is an agglomerative hierarchical method called the Ward's method (Aldenderfer & Blashfield, 1984; Van Ryzin, 1995). The method starts with individual words and then forms clusters by grouping these words into larger categories according to the assessment of similarities among these words.

As discussed above, the clustering results cannot be fully interpreted or applied without human evaluation. Thus after clustering, the study then applied evaluation of the clustering based on "supervised learning standards" that compare the categories resulting from the cluster analysis with pre-chosen categories by human coders. It then compared the clusters with the four large categories of information to figure out the types of information that were communicated. In addition, two expert coders were hired to evaluate and independently categorize the same sets of clusters for validation.

Next, the study examines the tweets of 100 nonprofits on the Topnonprofits.com 100 list, which ranks organizations by social media impact, website traffic, and Charity Navigator ratings (Topnonprofits, 2015). The 2015 Topnonprofits 100 list data are collected for each nonprofit from all seven measured criteria (i.e., Facebook Likes, Twitter Followers, Moz Page Rank, Moz Linking Root Domains, Alexa Rank, Google PageRank, and Charity Navigator Ratings). The 2015 Topnonprofits 100 list is determined by giving a one third-weight to social media (Likes and Followers), a one third-weight to overall website rankings (Moz Page Rank, Moz Linking Root Domains, Alexa Rank, Google PageRank) and a one-third to Charity Navigator Ratings. The Topnonprofits (2015) provides a detailed methodological explanation of the Topnonprofits 100 list. The study uses the Topnonprofits 100 list to understand the communication via information channels like websites and social media because these 100 nonprofits were the most visible organizations online and they had the largest numbers of website visitors and social media followers in 2015 (the most recently available year at the time of this study).

The organizational names are the keywords searched on Twitter using the same R program mentioned above. For instance, the Save the Children Federation Inc. is one of the Topnonprofits 100 listed organization. To download tweets about the Save the Children Foundation, “savethechildren” is searched as the key word for the organization. One reason for searching in such a way is the consideration of the two-way communication on Twitter. The official Twitter account of the organization is @savethechildren. However, @savethechildren is not the only account that tweets about the organization. Individuals can also use their own accounts to tweet about “savethechildren” besides retweeting and replying to the tweets generated by the organization. Therefore, searching and downloading the key words instead of the tweets sent by the official organizational account allows for capturing the two-way communication, which fits the purpose of this study. 6,000 tweets for each organization were downloaded through various dates between April 26 and May 13, 2016 (3,000 downloaded on April 26, and 1,000 each on May 3, May 8, and May 13). The study uses the data to explore the types of information used by nonprofits and the public to communicate with each other. To analyze tweets communicated about the Topnonprofits 100 organizations, the study employs the same analytical procedure used for analyzing "donation" and "fundraising".

3.3.2 Tweets of "donation" and "fundraising"

The primary message from analyzing tweets about "donation" and "fundraising" is that direct requests and mission-related information are communicated more frequently than financial and performance-related information. For example, the word cloud of "donation" shows that the two most frequently tweeted words are "thanks" and "blood" (Figure 3-1). In a word cloud, the most frequently appearing words are shown in the biggest font size (for example, see Li & Van Ryzin, 2017).

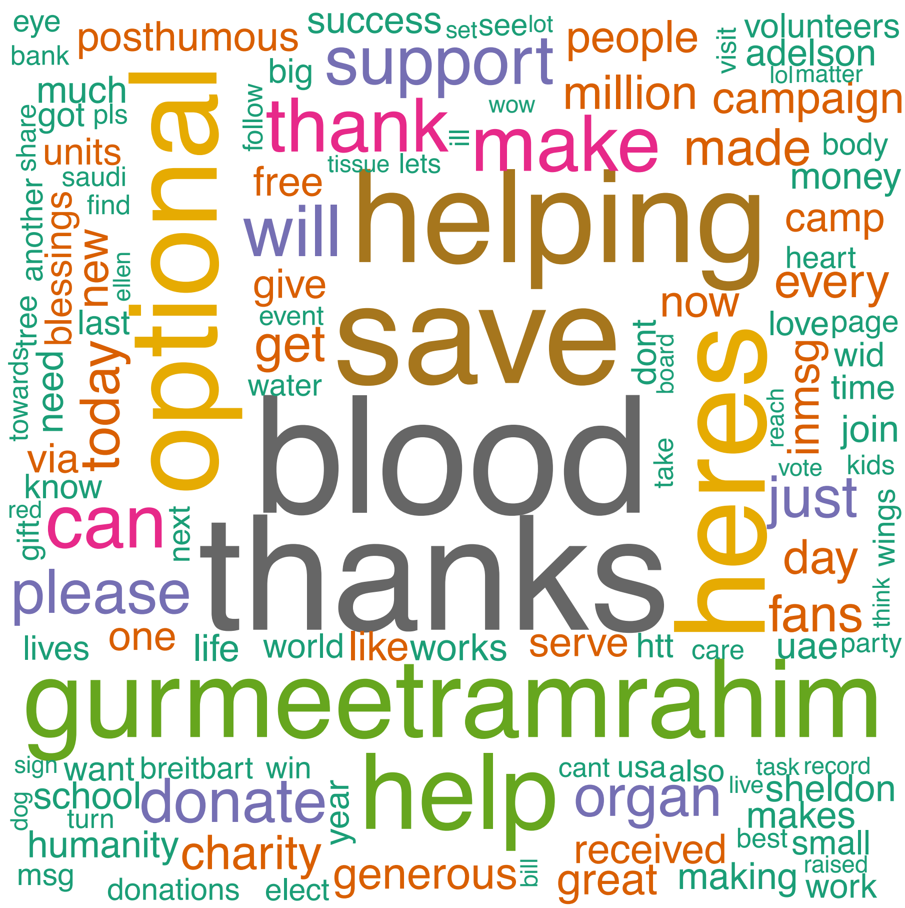


Figure 3-1: The word cloud of donation. The font size represents the frequency of a word appearing in the dataset. The bigger the font size, the more frequently the word appeared. In this word cloud, “thanks” and “blood” are the most frequently tweeted words.

“Thanks” is a very typical word used in direct requests. “Blood” is commonly a cause related to organizational mission. For instance, a user named “MiNiMint1218” retweeted a tweet generated by another user “gargvandu7” on March 1, 2016 saying “On pious #MahaRehmoKarmDiwas @derasachasauda organizing blood donation camp to fulfill needs of different blood banks.” This tweet was then retweeted 88 times on the same day. Clearly, “to fulfill needs of different blood banks” was the mission of the “blood donation camp” mentioned in the tweet. Another example was the user “Gurmeetramrahim” who tweeted “#MSGmissionHumanity Commendable work by volunteers!! Blood donation to serve mankind. GREAT!! Blessings to all.” on May 16,

2016. The tweet then became a popular one and made “gurmeetramrahim” a frequently used word in the word cloud. The hash tag # MSGmissionHumanity used by “Gurmeetramrahim” contained the word “mission” and clearly showed the close connection between “blood” and “mission”. Therefore, “blood”, is categorized as mission-related information in this study.

Figure 3-2 presents the clusters of “donation” and also shows that communications about “donation” use more direct requests and mission-related information than other types of information. In Figure 3-2, there are ten clusters from top to bottom. The first cluster has words like “thanks” and “helping” which are typically used in direct requests. The second cluster has the word “blood”, a commonly used theme word in mission-related information. The third cluster has the word “Gurmeetramrahim”, which as mentioned above, is actually the ID of a Twitter user who posted a popular tweet about “blood donation”, which is mission-related. The fourth cluster has words such as “service”, “passion”, and “success” that also frequently appeared in mission-related information.

The fifth cluster includes words like “fans”, “msgmyandurchoice”, “blessings” and “humanity” that are categorized into mission-related information. “Msgmyandurchoice” comes from the hash-tag “#MSGMyAndUrChoice” that encourages people to be blood donors. This “#MSGMyAndUrChoice” was initiated by the user “Gurmeetramrahim” and then became a campaign for blood donation. For example, user “JyotiBhayana1” tweeted on February 7, 2016 “#MSGMyAndUrChoice Blood donation<><><><>giving someone's new life... And that great task only can do DSS Volunteers!!!”, which specified the mission of “blood donation” as “giving someone’s new life”. Therefore, the cluster is categorized as mission-related information.

The sixth cluster has words like "million, adelson, sheldon" that are excluded from analyses due to their irrelevance to nonprofit communications. The cluster is actually about Adelson Sheldon who pledged to donate 100 million dollars towards electing Donald Trump president in the 2016 election. That "political campaign" was captured first by the R program and then clustered because of its high frequency of tweets, but it is not a theme studied here.

The seventh cluster has a lot of words and shows a mixed format of different types of information – words such as "money", "great", "makes", "making", and "made", which might be regarded as either financial or performance-related information. Other words, like "organ" and "school", demonstrate clearly that they are mission related information. To illustrate the point that various types of information are actually communicated simultaneously, here the study categorizes the seventh cluster into both financial and performance information.

The eighth cluster "help" and the ninth cluster "thank" can also be categorized into direct requests, as shown in the first cluster. The words in the ten cluster – make, will, support, donation, and please – are usually seen in direct requests.

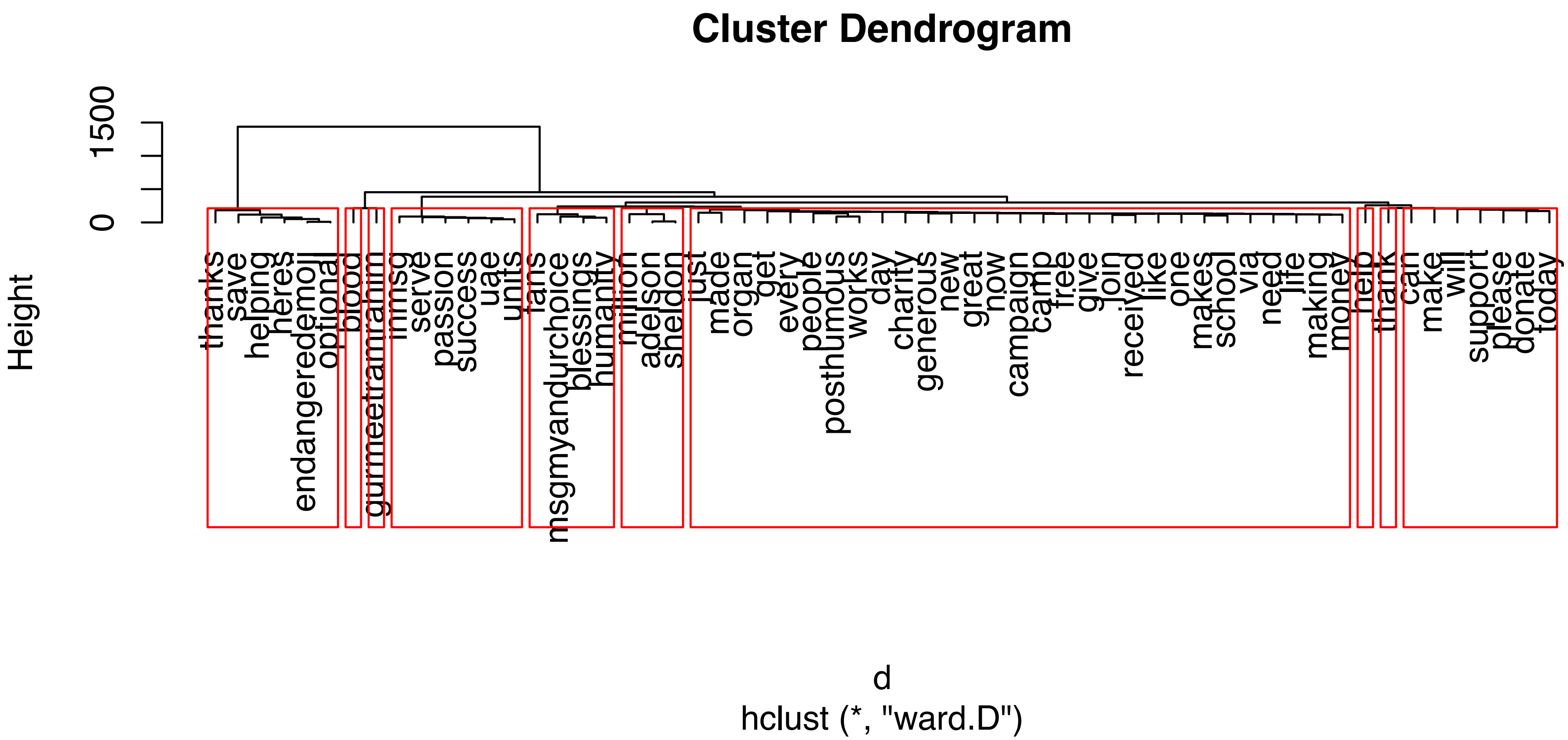


Figure 3-2: Clusters of "donation". The ten-diagram dendrogram of clusters with each of the most frequently appearing words on the left and then nested hierarchically to the right. The method used for clustering is Ward's method, which starts with individual words and then forms clusters by grouping these words into larger categories according to the assessment of similarities among these words (for an example, see Li & Van Ryzin, 2017).

In sum, when nonprofits and the public are tweeting about “donation”, 40% of the information communicated (4 out of 10 clusters) is mission-related information, 40% is direct requests, followed by performance-related information and financial information at 10% each.

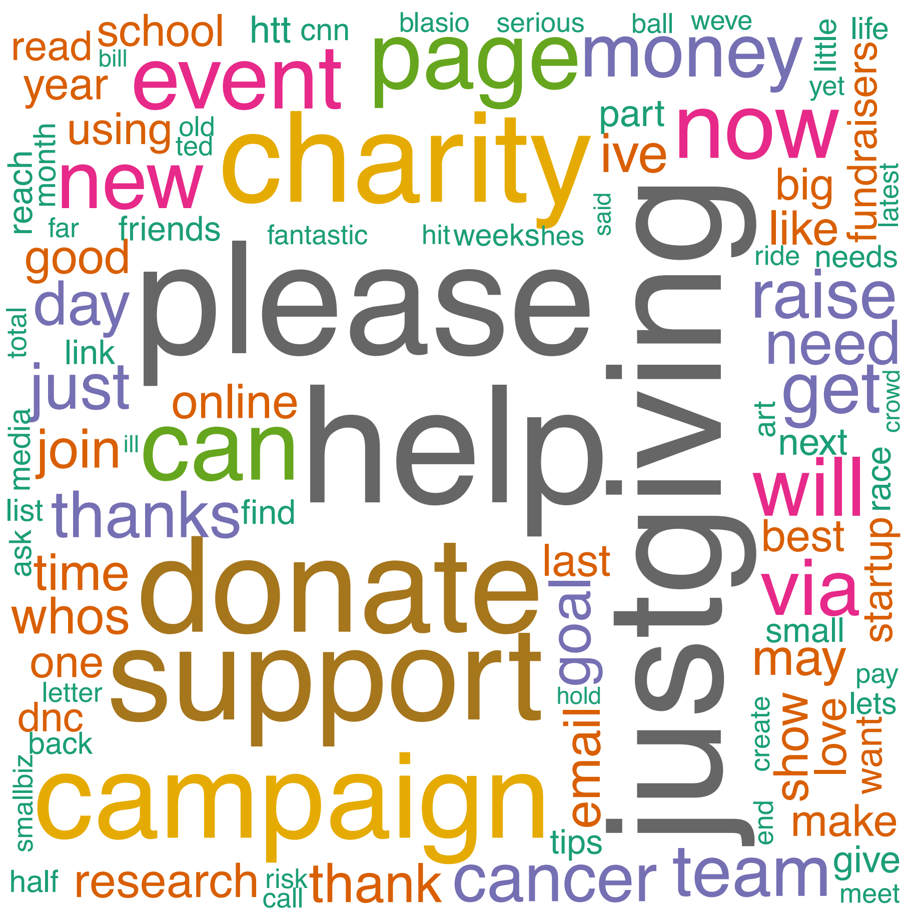


Figure 3-3: The word cloud of fundraising

Applying the same analytical procedure to analyze communicated tweets about “fundraising”, a similar communication pattern emerges. Figure 3-3 shows that the most frequently tweeted words are “please”, “help”, and “justgiving”, which are commonly seen in direct requests. “Justgiving”, which is an account representing Justgiving.com on Twitter, is a crowd-fundraising service. “Justgiving” lets people in financial need set up justgiving pages on its website and then promotes the pages on Twitter and many other online platforms. In other words, “justgiving” is an online professional service for fundraising and requests donations directly from the public. Apparently, “justgiving” uses many types of information other than direct requests. But undoubtedly, direct requests are the most common information type communicated by “justgiving”. Therefore, the first takeaway from the word cloud of “fundraising” is that direct requests are the most frequently tweeted communications about “fundraising”.

After clustering the most frequently tweeted words compromising 99.99% of 500,000 tweets about “fundraising”, it can be seen that like the results found from analyzing clusters of “donation”, direct requests and mission related information are most commonly used by nonprofits and the public (Figure 3-4). Financial information and performance related information appear much less frequently. The first cluster is not easy to categorize. It includes many words like “money”, “million”, “raise”, “raised” and “raising” that can be treated as pieces of financial information; yet it also it includes words like “cancer” and “research” that are mission-related, since cancer research is a benevolent cause and obviously deserves money.

The second to seventh clusters, each contains only one word: “charity”, “campaign”, “support”, “help”, “please” and “donate”, in that order “Charity” is commonly a mission-related word; the rest can all be categorized as direct requests. The eighth cluster has the words “who’s”, “justsponsored” and “now”, which were words seen in the “justgiving” campaigns launched by Justgiving.com. These words, as well as the word "justgiving" in the ninth cluster, can also be recognized as direct requests. Additionally, "using" and "check" relate to direct requests. Therefore, the eighth, ninth and tenth clusters are all categorized as direct requests. Results from content analyses of the clusters of fundraising show that the vast majority of messages communicated are direct requests (80% clusters). Mission related information occupies another 10% of the clusters. The rest of the clusters' content (10%) is financial information.

This section shows that direct requests such as "help, please, thanks" are the most commonly tweeted information type when people tweet about donation and fundraising, followed by mission-related information, performance-related information, and financial information.

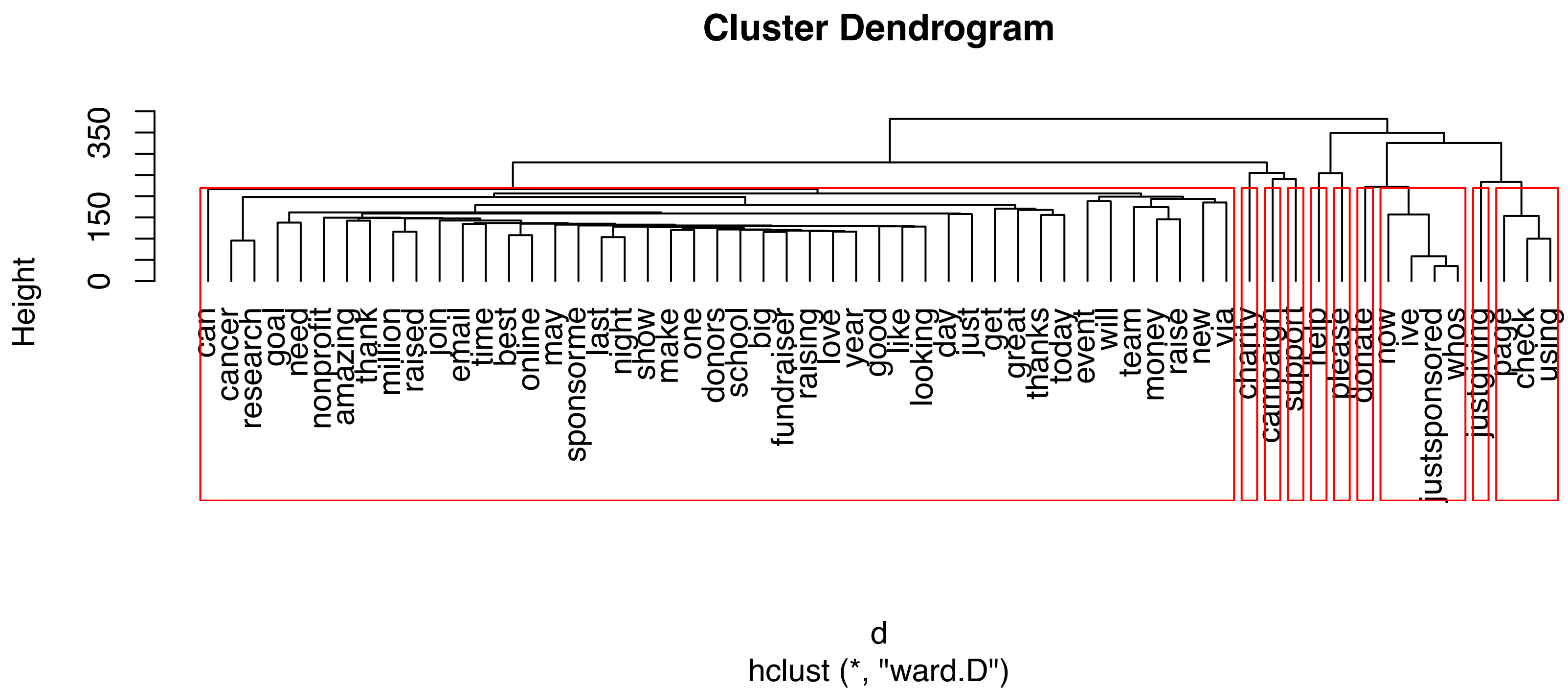


Figure 3-4: Clusters of fundraising.

3.3.3 Communications between nonprofits and the public on Twitter

To figure out what types of information were communicated via tweets between the Topnonprofits 100 organizations and the public, the same coding procedures are used for analyzing “donation” and “fundraising”. Figure 3-5 is an example of the coding procedure that shows the analytical method applied in studying “UNICEF”. After downloading the 6,000 tweets about “UNICEF” through various periods, the study first creates the word cloud to capture the most frequently tweeted information, then clusters them into ten dendrongrams, and finally, categorizes ten dendrongrams into four types of information: mission-related information, direct requests, financial information, and performance-related information. As mentioned above, the basic organizational information type is excluded because of the non-presence of such information on communicated tweets. Frequencies of each type of information are also calculated for further analyses.

As shown in Figure 3-5, eight clusters are formed by the mission-related information, one is made of direct request and the other is comprised of performance information; none was in the category of financial information. The first cluster includes the words “katyperry, energy, giving, instead, dontfeedthebe, conspiracy, eyeballs, check, dumb”. Katy Perry is an American pop star who together with UNICEF launched a word game in April 2016 on Twitter to increase parents’ awareness of the importance of childhood learning. A typical retweet reads, “RT @katyperrylately: VIDEO: Word game with Katy Perry | @UNICEF https://t.co/fu0Nq0PwqA”. This “word game” is asking individuals to support the UNICEF by playing the game. Therefore, the study categorizes this cluster as a direct request.

The second cluster is about providing aid for children to play soccer. “Socceraid” is another project related to UNICEF’s mission. The second cluster is thus also identified as mission-related information. Words “southsudan, conflict, families, unicefsudan” form the third cluster. This cluster, which is about families that needed help during the Sudan conflict, identifies a specific need related to the organizational mission. It thus is categorized as mission-related information. Similarly, the fourth, sixth, seventh, and tenth cluster all describe certain social needs in Syria, Ecuador, and Yemen, respectively. Therefore, all four of these clusters are also categorized as mission-related information.

The fifth cluster is about a special event launched on Mothers’ Day to thank mothers for their selfless support to children, which is also a piece of mission-related information. The eighth cluster, which has only one word, “children”, clearly demonstrated UNICEF’s mission to help children all over the world.

The ninth cluster is about increasing people’s access to safe water. The fact that nearly half of all people can drink safe water shows the performance of UNICEF’s work. Thus, it is recognized as a piece of performance-related information.

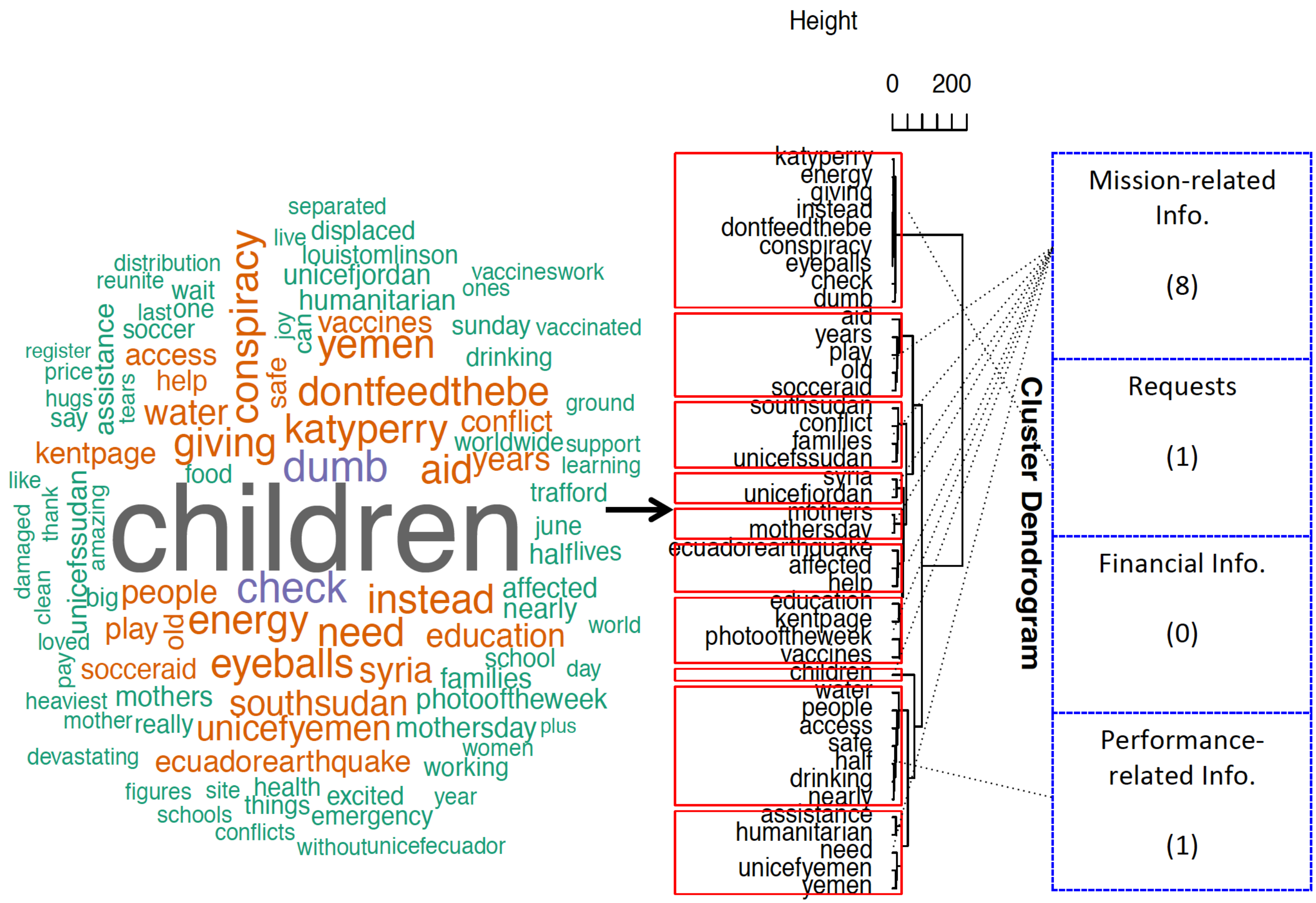


Figure 3-5: The coding procedure. The analytical procedures of big data say to first create a word cloud of a nonprofit organization; then cluster the most frequently communicated items; and finally, categorize the clusters into pre-determined categories.

Following the same coding procedure (Figure 3-5), the study then code 1,000 clusters into four different categories of information (10 clusters for each of the 100 nonprofit organizations. See Appendix for more details about all the clusters). Table 3-1 presents the results, which clearly show that mission-related information and direct requests are used more during tweeted communications.

Table 3-1: Descriptive statistics of different types of information on Twitter

	Min	Max	Mean	Percentage
Mission	4	10	7.69	76.9
Request	0	6	1.74	17.4
Performance	0	3	0.42	4.2
Finance	0	3	0.15	1.5

Note: All numbers are calculated based on frequencies of clusters.

The minimum frequency of mission-related information is 4, which indicates that, for each nonprofit, at least 4 clusters of communicated tweets are mission-related information; and the maximum frequency of mission-related information is 10. In other words, for some nonprofits, all of the most frequently communicated information is mission-related. Seventy-seven percent of the most frequent tweeted clusters are composed of are mission-related information, which means that almost eight out of ten clusters of communicated tweets about a single nonprofit organization are mission-related information. One reason why mission-related information is the most frequently communicated is because information about certain projects operated by an organization directly reflects its mission. The percentage of direct requests is 17.4. Compared to the high percentages of mission-related information and direct requests, the percentages of the other two types of information are relatively low. Percentages of performance-related information and financial information are 4.2 and 1.5, respectively.

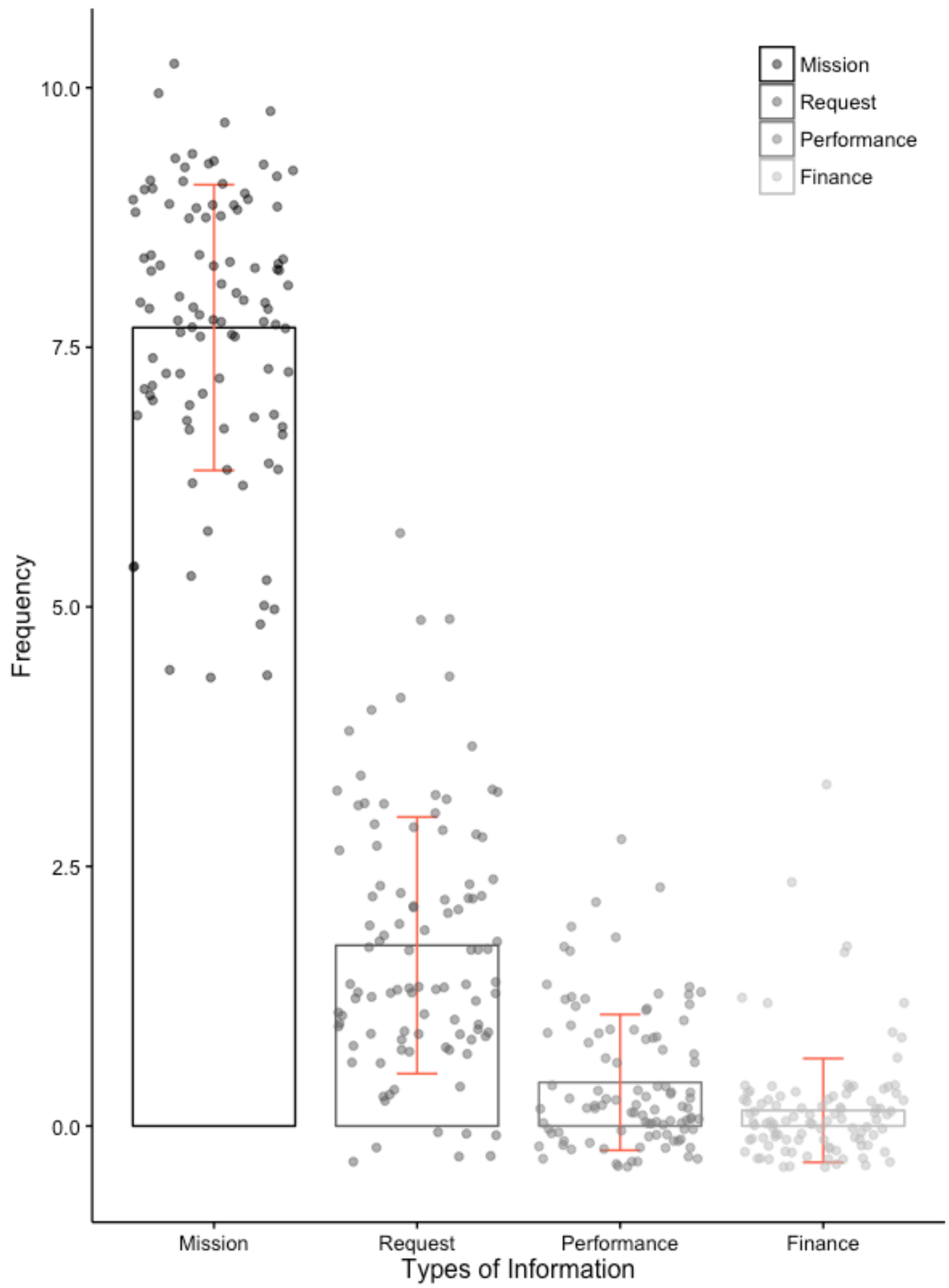


Figure 3-6: Distribution of different types of information on Twitter. Each dot represents the frequency of a certain type of information communicated about an organization. The bars represent the mean frequency values of each type of information with the error terms.

Figure 3-6 provides the visualized distribution of the frequencies of all the clusters and the mean values of frequency of information. Each dot represents the frequency of a certain type of information communicated about an organization. The bars represent the mean frequency values of each type of information with the error terms. Again, mission-related information and direct requests are communicated more than financial and performance-related information on Twitter. The study also conducts a one-way ANOVA test and finds significant differences among the means of all the groups of different types of information ($p < .001$). Of course, the results might undermine the use of financial and performance-related information since only words communicated more than 99% frequency were clustered. However, among the most frequently tweeted information, mission-related information and direct requests appear to be communicated more than other types of information. Thus, the study concludes that mission-related information and direct requests are more likely to be communicated between nonprofit organizations and the public on Twitter than financial and performance-related information.

3.4 Why Cheap Information Is Tweeted More Than Costly Information?

Why are mission-related information and direct requests used more during communications than financial and performance-related information? One explanation is that mission-related information and direct requests are cheaper than financial and performance-related information. The costs associated with communicating mission-related information and direct requests for contributions are relatively lower, especially, when doing so online. After setting up the initial social network services and websites, for which organizations have to pay the service fees, the costs of sharing such information online can almost be neglected. The study thus labels mission-related information and direct requests as “cheap information”. On the other hand, financial and performance-related information are usually produced at higher costs because of auditing and accrediting services. And to communicate financial numbers and performance indicators is often more difficult than reinforcing your mission or simply asking for contributions because of the complexity of financial numbers and common disagreement on performance measurement. In addition, individuals have to use system 2, which costs more brain resources and human energy (Kahneman, 2011), to process financial and performance-related information, especially, when they are in numerical or statistical formats. Therefore, both financial and performance-related information are labeled as "costly information".

Another explanation is that nonprofits strategically communicate customized information with targeted audiences to increase donations. As mentioned above, nonprofits tweet to achieve various desirable goals, such as advocating (Guo & Saxton, 2014), branding (Waters et al., 2009), engaging stakeholders (Lovejoy & Saxton, 2012; Lovejoy et al., 2012) and fundraising (Nonprofit Marketing Guide, 2016, 2017). Fundraising to increase donations is the focus of this study because donations signal a bundle of information that includes donors' awareness of nonprofits, trust in nonprofits and willingness to donate. In other words, donation is a good measurement of both money contributed to nonprofits and donors' awareness and trust of nonprofits. The study presents a simple model based on a "cheap talk game" (Farrell, 1995; Farrell & Rabin, 1996) and assumes that a nonprofit organization is more likely to deliver "cheap information" online due to the costs of information sharing and information consumption.

In a simplified game, the nonprofit assumes that donors who surf the web or social media do not have patience to engage in deep discussion and thus are less likely to be interested in costly information. In other words, individuals online are only interested in cheap information. The organization also assumes that donors who request information from the organization via mail, phone, and visit are more likely to engage in deep conversations and consume costly information.

On the donors' side, this study assumes there exist two different types of donors: cause-driven, self-centered Type I donors and outcome-driven, altruistic Type II donors. Type I donors are likely to be motivated by information that makes them feel good. Being asked for help and then help to solve social problems both make people feel good. Therefore, direct request and mission-related information are assumed to meet the information needs of Type I donors. Pure altruists (Andreoni, 1989), on the other hand, calculate the financial numbers and weigh the performance of the organization to better allocate their contributions to make a larger social impact.

Communication benefits both parties by reducing information asymmetry and enhancing mutual trust and thus co-produces better outcomes. However, mismatched communication between nonprofits and donors cannot generate such desirable results. The model has four possible outcomes, corresponding to nonprofits' communication strategies (cheap or costly information) and donors' types (Type I or Type II). For each possible outcome, the study first presents gains for nonprofits and donors' payoffs and then makes a strong assumption that donors' payoff does not vary. The payoff is (m) and is consistent in both cases. To further simplify, the model assumes that both parties will get nothing when there is a miscommunication between them. For instance, if a nonprofit organization delivers cheap information to a Type II donor who is seeking costly information, there will be no gains for either party. There are two pure-strategy Nash

Equilibriums at (Cheap information, Type I) and (Costly information, Type II). At the (Cheap information, Type I) equilibrium, nonprofits gain (x) and Type I donors gain (m); and at the (Costly information, Type II) equilibrium, nonprofits gain (y) and Type II donors also gain (m).

		Donors	
		Type I	Type II
NPOs	Cheap information	(x, m)	(0,0)
	Costly information	(0,0)	(y, m)

However, there could exist a mixed-strategy Nash Equilibrium where nonprofits could use cheap information strategy at probability (*p*) and costly information strategy at probability (*1-p*) to yield the same outcomes. The probability (*p*) is then determined by the following equation:

$$(p\times x) + [(1-p)\times 0] = (p\times 0) + [(1-p)\times y]$$

Based on the above equation, $p = \frac{y}{x+y}$. To summarize, if there is a mixed-strategy Nash Equilibrium, then nonprofits are mixing the strategies with weights $\left(\frac{y}{x+y}, 1 - \frac{y}{x+y}\right)$ on cheap and costly information, respectively. The study also sets another restriction that y is usually larger than x $(y > x)$ since nonprofits strategically use costly information to solicit bigger donations. Then we have $(\frac{y}{x+y}) > (1 - \frac{y}{x+y})$ corresponding the fact that cheap information is tweeted more than costly information. To solve the inequality, we have $(y > x)$ that meets the restriction. In sum, if nonprofits are mixing both cheap and costly information communication strategies on Twitter, and if the costly information strategy yields higher payoff, then nonprofits are likely to tweet more cheap information.

This simple model can be extended to describe more complex situations.

According to this model based on the "cheap talk" game, nonprofits strategically target donors to communicate with them specific types of information to meet these donors' needs, reduce information asymmetry, and build and enhance mutual relationships to solicit their charitable contributions. This alternative explanation suggests that nonprofits communicate more mission-related information and direct requests online not only because of the information costs but also because of nonprofits' organizational communication strategies, which assume there are more Type I donors online. To validate this argument, further evidence about characteristics of individuals who are online is needed.

3.5 Is Communicating More Cheap Information Useful?

Based on the above discussion, a follow up question is whether such communications – tweeting more cheap information – are useful? To answer this question, this section examines the relationships between frequencies of various types of information and the public attitudes toward nonprofits, a measure used to predict donations to nonprofits (Webb, Green, & Brashear, 2000). On one hand, because the information is "cheap", general donors do not learn a lot from mission-related information and direct requests for donation. Therefore, cheap information might not be useful for facilitating giving decisions, even communicated more frequently. On the other hand, even though it is cheap, these tweets provide information that increases organizational transparency, which helps enhance donors' trust in nonprofits and translates into more donations. For example, the IRS also assumes that mission-related information has positive impacts on donations (IRS, 2008). However, the lack of empirical evidence prevents us from better understanding the effectiveness of communicating cheap information. This section first hypothesizes that: *More cheap information is associated with more positive public attitudes toward a nonprofit (higher sentiment scores)*.

Table 3-2: Descriptions of variables

Variables	Descriptions	Data Sources	N	Mean	S.D.	Min.	Max.
Dependent variable							
Sentiment scores	$(\frac{positive}{positive+negative})$*100	Author	100	73.24	23.23	9	100
Sentiment scores (dummy)	0 if scores <= 80; 1 if > 80	Author	100	0.51	0.50	0	1
Independent variables: frequencies of types of information							
Cheap information	Frequencies of mission-related information and direct requests combined	Author	100	9.43	0.78	7	10
Cheap information (dummy)	0 if frequencies <= 8; 1 if > 8	Author	100	0.58	0.50	0	1
Mission	Mission-related information	Author	100	7.69	1.38	4	10
Request	Direct requests	Author	100	1.74	1.24	0	6
Performance	Performance-related information	Author	100	0.15	0.50	0	3
Finance	Financial information	Author	100	0.42	0.65	0	3
Control variables							
Twitter followers	Number of Twitter followers (k)	Topnonprofit.com	100	507.66	838.29	12	4,900
Areas	NTEE 10 categories	IRS	100	4.53	2.05	0	8
Size	log(total assets)	IRS	97	18.14	3.28	0.00	22.84
Age	IRS rule dates	IRS	97	41.17	22.84	8.98	94.97

Note: Sentiment scores, both in continuous and dichotomous forms, are used as dependent variables. The frequency of cheap information is calculated by combining together the frequency of mission-related information and the frequency of direct requests. The unit for number of Twitter followers is thousands. For the areas to which nonprofits belong, the study uses the NTEE major 10 categories: AR (Arts, culture, and humanities), ED (Education), EN (Environment), HE (Health), HU (Human services), IN (International), MU (Mutual benefit), PU (Public and societal benefit), RE (Religion), UN (Unknown). UN is then used for the reference category and is coded as “0”. The size of a nonprofit is measured by taking a log of its total assets. And the rule dates – coded reversely – are used as a measure of organizational ages.

To test the hypothesis, the study uses sentiment scores to measure the effectiveness of communications on Twitter. Sentiment scores are calculated from all tweets communicated between nonprofits and the public by using the function: $\left(\frac{numbers\ of\ all\ positive\ words}{numbers\ of\ positive\ words + numbers\ of\ negative\ words}\right) \times 100$. The study then regresses sentiment scores on frequencies of cheap information to investigate whether more cheap information associates with higher sentiment scores. Table 3-2 presents the descriptions of the variables used in regression models.

The regression results (Table 3-3) show that communicating more cheap information is not associated with the public attitudes toward nonprofits. Moreover, none of the frequencies of various types of information correlate the sentiment scores that measure the public attitudes toward nonprofits.

More direct requests are slightly associated with more positive attitudes toward nonprofits (also see Figure 3-7). Frequencies of mission-related information, performance-related information, and financial information are slightly negatively correlated with attitudes toward nonprofits. All of the results, however, are not statistically significant. Therefore, this study rejects the hypothesis that "*More cheap information is associated with more positive public attitudes toward a nonprofit (higher sentiment scores).*"

Table 3-3: Regression results

	Public Attitudes (Sentiment scores)											
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Cheap info.	0.74						1.18					
	(3.00)						(3.03)					
Mission		-1.62						-1.82				
		(1.70)						(1.84)				
Request			2.30						2.45			
			(1.89)						(1.91)			
Costly info.				-0.74						-1.18		
				(3.00)						(3.03)		
Finance					-0.19						3.48	
					(4.70)						(4.51)	
Performance						-0.95						-4.24
						(3.59)						(3.74)
Controls: Numbers of Twitter followers, NTEE major 10 categories, Organizational size, and age												
	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100	100	100	100	100	100	97	97	97	97	97	97
R^2	0.001	0.009	0.015	0.001	0.00002	0.001	0.226	0.234	0.240	0.226	0.230	0.236

Note: *p<0.1; **p<0.05; ***p<0.01. Standard deviation in parentheses.

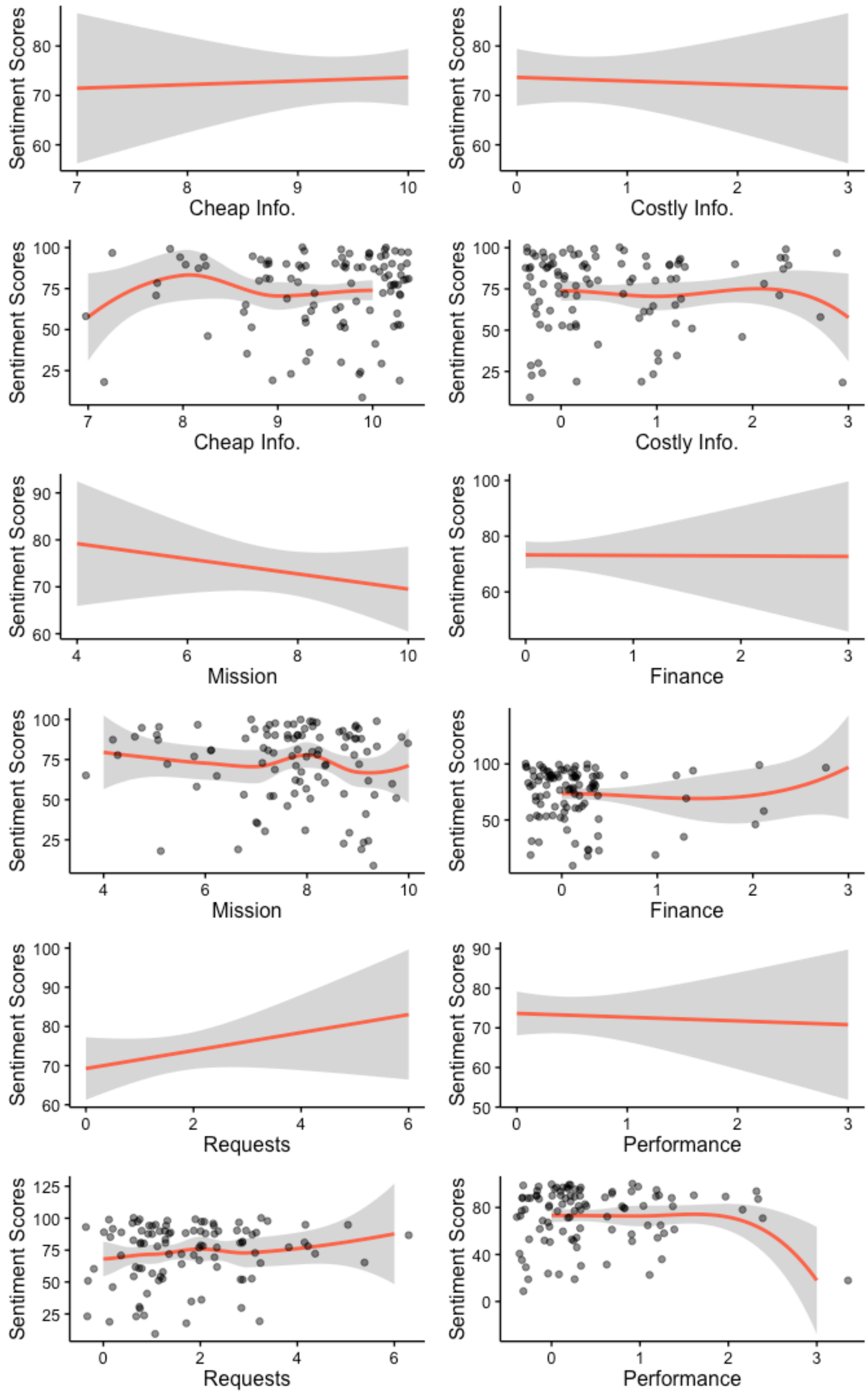


Figure 3-7: Relationships between frequencies of information and sentiment scores. Plots of linear relationships between frequencies of information and sentiment scores are presented above the plots of nonlinear relationships. The grey zone in each plot represents the 95% confidence interval.

As shown in Figure 3-7, both the skewed distribution of frequencies of various types of information and the non-linear relationships between frequencies of information and the public attitudes toward nonprofits contribute to the no significant findings presented in Table 3-3. For example, most of the 100 nonprofits studied here communicate more than eight out of ten times with cheap information, which causes the skewedness of the distribution. In addition, the distribution of the frequencies of cheap information is not linear. The study also checks the robustness of the results by using dichotomized dependent variables and the dichotomized measure of the frequency of cheap information (See Appendix B) and confirms the robustness of the results.

3.6 Conclusion and Discussion

The study first answers what types of information are being communicated online between nonprofits and the public. Based on the results of analyzing the general communications about “donation” and “fundraising” and the communications of about 100 nonprofit organizations on Twitter, the study first finds that four types of information – mission-related information, direct requests for donations, performance-related information, and financial information – are frequently communicated online between nonprofits and the public. The study further finds that mission-related information and direct requests are more frequently communicated online than financial and performance-related information. There are differences between the general communications about “donation” and “fundraising” and the communications around the Topnonprofits 100 organizations. When organizations and individuals tweet about “donation”, 50% of the most frequently tweeted information is direct requests. The number goes up to 80% when communications about “fundraising” are tweeted. In terms of the specific communications around the Topnonprofits 100 organizations, results suggest that, instead of direct requests, mission-related information is the most frequently communicated information. 76.9% of the information communicated on Twitter about the 100 nonprofit organizations is mission-related information. Despite the slight differences, mission-related information and direct requests are more likely to be used in online communications between nonprofits and the public.

The study then suggests two alternative explanations of why mission-related information and direct requests are favored during the online communications between nonprofits and the public: the "information sharing costs" perspective and the "cheap information" theory. The former perspective suggests that mission-related information and direct requests are favored because of the lower costs of producing and sharing them online; while the later one suggests that they are more likely being communicated because nonprofits are strategically using more "cheap information" online, which meet the exact information needs of Type I donors. The study presents a model based on the cheap talk game to elaborate the second approach.

In order to examine the effectiveness of such communications, the study also tests the relationships between frequencies of various types of information and the public attitudes toward nonprofits measured by the sentiment scores. The results show no significant associations between frequencies of information and the public attitudes toward nonprofits, which imply that more mission-related information and direct requests are not effective in increasing donations to nonprofits. The study thus suggests that frequencies of information might not have impacts on donors' attitudes toward nonprofits.

Limitations

The investigation presented here is not without limitations. The first limitation is that all the tweets are collected from the same year (2016). Communications about "donation" and "fundraising" and the Topnonprofits 100 organizations in 2017 may be very different from in 2016. As mentioned, 2016 is a presidential election year during which political campaigns actively used "donation" and "fundraising" to communicate with political supporters. After eliminating the tweets related to presidential candidates from both Democrats and Republicans, there is still a possibility of biased results.

Additionally, only 6,000 communicated tweets about each nonprofit are downloaded. The number is relatively small for big data analyses, such as for creating word clouds and clusters. The number of downloadable tweets is restrained by the fact that Twitter only allows free APIs, which the study used, to retrieve tweets within seven days.

Another limitation is about the relative small sample size that contains only 100 nonprofits from the Topnonprofits 100 list. As for the 100 organizations, the ranking could change in 2017 due to many factors such as organizations getting or losing more Twitter followers, improving their Alexa page rankings, and improving their Charity Navigator star rankings. If the list of the 100 nonprofits changes in 2017, then the tweet data from 2017 cannot be paired with the tweets data from 2016. In addition, regression results based on a small sample size have limited external validity and cannot be generalized and applied to other situations without cautions.

It should be also noted that the study does not directly measure donations. Instead, it uses sentiment scores to measure the public attitudes toward nonprofits. Even though positive public attitudes usually predict increases in donations well (Webb, Green, &

Brashear, 2000), indirect measures of donations cannot provide empirical evidence on relationships between frequencies of information and donations.

In addition, sentiment scores are proxies to public attitudes due to the fact that the machine learning processes cannot fully process the natural language accurately, even supervised. For example, an organization can have a very positive mission but with many negative words, resulting in low sentiment scores. Nonprofits like heart association and cancer association will repeatedly communicate negative words such as “cardiovascular diseases and stroke” and “cancer”, respectively. The public, however, usually has very positive attitudes toward these associations. Therefore, it should be noted that there is also a possible bias associated with using sentiment scores to measure public attitudes.

Future research

To include more nonprofits in the United States would improve the validity and generalizability of the study. For example, future studies can extend the sample to include the nonprofits listed in the NCCS dataset (NCCS, 2015). Building a panel of data of more communicated tweets about these nonprofits at the same time periods across various years would certainly improve the study. Therefore, future studies should use the “bigger data” about more nonprofit organizations collected from multiple years to see whether it will result in similar conclusions about online communications between nonprofits and the public.

With the current dataset, future research can combine the quantified qualitative data such as communication frequencies of certain types of information with other data on nonprofits, such as data retrieved from IRS 990 forms, to estimate the effects of various types of information on donations. Then, actual dollar amounts can be used to measure donations directly. In addition, sentimental scores calculated from communicated tweets can also be incorporated into such data to figure out whether social media communications will influence donations to nonprofit organizations.

CHAPTER 4: NUDGING SAMARITANS: A CONJOINT EXPERIMENT

4.1 Introduction

Communication plays an important role in addressing the issue of information asymmetry between nonprofits and the public. Information asymmetry often discourages individuals' donations to nonprofit organizations. For those nonprofits that want to increase donative revenues, a primary concern of effective nonprofit communication strategies is to communicate customized information with targeted donors to satisfy donors various information needs.

Existing literature has investigated the impact of various types of information on donors' giving decisions. Saxton and colleagues found that donors are significantly more likely to respond to financial information than to performance-related information (Saxton, Neely, & Guo, 2014), which contradicted previous research (McDowell, Li, & Smith, 2013). Existing literature recognized the importance of financial and non-financial information (performance-related and mission-related information). However, there is no consensus on which information is more influential on donors' giving decisions.

In addition, to date, far too little attention has been paid to the impact of particular types of nonprofit information on different types of donors. In this study, donors were categorized into two types: (1) Type I donors, who respond more to nonprofit mission and enjoy the good feelings about their own giving actions, and (2) Type II donors, who pay attention to the outcomes and performance of nonprofits that they donate money to. Performance-related information might have a larger impact on donors who pay attention to organizational outcomes and performance than on those who are sympathetic donors

(Rose-Ackerman, 1982, 1996). “If sympathy is the dominant motivation, individualized stories of hardship should be most effective. If commitment dominates, reports on the overall effectiveness of the organization’s programs are needed”, argued Rose-Ackerman (1996, p. 714).

Despite the importance of different types of nonprofit information and strategies of communicating the customized information with targeted donors, there remains a paucity of empirical evidence on the influences of certain types of information on donors as a whole and on different types of donors. In this study, a conjoint experiment was employed to test the impact of four different types of organizational information—mission-related information, direct requests for donations, performance-related information, and financial information—on donors’ decisions. The experimental results show that donors are more responsive to direct requests for donations, more highly evaluated missions, higher performance ratings, and higher program ratios. And there is no significant difference between Type I donors and Type II donors in responding to various information.

The remaining part of this chapter proceeds as follows. Section 4.2 reviews the relevant literature. Section 4.3 introduces the conjoint experimental design. Results are presented in section 4.4. Section 4.5 concludes.

4.2 Literature

4.2.1 Information contents

Previous chapters did not investigate the influence of the content of information on donors’ decisions. In Chapter 3, four different types of information about nonprofit organizations were identified and discussed: mission-related information, direct requests for donations, financial information, and performance-related information. Chapter 3 then tested the impact of frequencies of each type of nonprofit information communicated between the Top 100 nonprofits and Twitter users' attitudes toward these organizations. Chapter 3, however, did not study the impact associated with the content (i.e., message) of the communicated information.

Content of information matters in effective communication, which reduces information asymmetries, enhances mutual trust, and, thus increases donations to nonprofits.

Highly evaluated missions matter. Different charitable causes appeal to different donors. This is usually reflected in nonprofits' missions. In the United States, if a nonprofit organization is granted the 501(c)3 status by the Internal Revenue Service (IRS), it must be organized for one or more of the following purposes according to the Tax Revenue Act of 1917: charitable, religious, educational, scientific, prevention of cruelty to children and animals, literacy, testing for public safety, and fostering national or international amateur sports competitions (IRS, 2008). This law acknowledged different charitable causes that are appealing to different donors. Some donors are more responsive to health-related organizational missions while others may be more attracted by nonprofits working to improve the conditions of children. According to a Giving USA report (GivingUSA, 2015), about 32% of the total individual giving in 2014 went to religious organizations, followed by education (15%), human services (12%), gifts to foundations (12%), health (8%), public-society benefit (7%), arts, culture, and humanities (5%), international affairs (4%), environment and animals (3%), and others (2%). It seems that aggregated individual donations value religious causes higher than the others.

Donors' evaluations of missions not only vary across different categories of nonprofit based on their National Taxonomy of Exempt Entities (NTEE) codes but also vary within one certain NTEE category (NCCS, 2015). For example, Pandey and colleagues showed the positive impact of carefully crafted organizational missions, measured by five mission statement attributes (activity, certainty, commonality, optimism and reality), on both the financial and non-financial performance of nonprofit performing arts organizations (Pandey, Kim, & Pandey, 2017). Another study, however, found mixed results about the influence of mission focuses on nonprofit financial performance (Kirk & Nolan, 2010). All three dimensions of mission focuses (the number of target audiences, the geographic scope, and the number of programmatic areas) influenced organizational financial indicators including overhead ratios, one-year changes in overhead ratios, and one-year changes in contributions, but in different ways. Kirk and Nolan showed that if mission statements focused more on geographic scope, nonprofits had lower overhead ratios; and if mission statements identified more target client groups, those nonprofits would have a larger one-year increase in total contributions. They also warned that in their findings, the associations between mission focuses were statistically significant but relatively weak, which questioned the common recognition of the importance of the mission statement to a nonprofit organization (Kirk & Nolan, 2010). However, previous studies did not examine the influences of evaluations of missions on donations. Thus, the first hypothesis of this study is:

H_1: More highly evaluated organizational missions are more likely to increase donations to nonprofits than lower evaluated missions.

The power of asking. Asking directly for donations to support a good cause is commonly seen in numerous nonprofit fundraising campaigns. An experimental study where one subject was asked to allocate ten dollars between himself or herself and a receiver who might or might not be able to speak found that any time the recipient asked, he or she would be given more shares (Andreoni & Rao, 2011). The study provided a piece of evidence of the "power of asking." Another study also found that 67% of Latino households and 68% of African American households had not given money or time to nonprofits because they were not "asked" (Havens, O'Herlihy, & Schervish, 2006).

However, people might also want to avoid being asked for donations. In a field experiment in which solicitors for the Salvation Army either simply rang their bell or verbally asked "please give" to passersby at entrances to a supermarket, researchers found that verbally asking for donations dramatically increased the amount of giving. However, verbally asking also significantly increased the avoidance of solicitation, between 26.2% and 32.6% (Andreoni et al., 2011). This study presents the second hypothesis here:

H_2: Simple direct requests are more likely to increase donations to nonprofits than no request.

Higher program ratios matter. Scholars have studied influences of nonprofit financial information on organizational performance. For instance, Saxton and colleagues found that the amount of financial and performance-related information disclosed on nonprofit organizations' websites was positively associated with the donations these organizations received (G. Saxton et al., 2014). Parsons and colleagues, in a series of works, studied the impact of financial (especially accounting) information on donations (Buchheit & Parsons, 2006; Parsons, 2003, 2007; Trussel & Parsons, 2007). For instance, Trussel and Parsons (2007) found that higher program ratios positively associated with more donations.

Why do donors prefer higher program ratios when such financial indicators are disclosed by nonprofits? One main reason is that donors care about whether or not their contributions can make a real difference in society and thus are more in favor of spending on programs instead of administrative activities (Bowman, 2006). The other main reason, slightly different from the reason mentioned above, is the positive priming effect of "program ratios" (Andreoni, 1995; Tversky & Kahneman, 1981). Therefore, donors tend to avoid overhead spending (Gneezy et al., 2014) due to negative framing effect or loss aversion (Kahneman, Knetsch, & Thaler, 1991; Tom, Fox, Trepel, & Poldrack, 2007; Tversky & Kahneman, 1991). Empirical evidence also shows that program ratios have the positive framing effect (Andreoni, 1995) and that higher program ratios have a larger impact in increasing donations to nonprofits (Bowman, 2006). This study, then, hypothesizes that:

H_3: Higher program ratios are more likely to increase donations to nonprofits than lower program ratios.

Better performance matters. "Although the measurement of performance is not a simple matter in any kind of organization, it is even more complicated for nonprofit organizations" (Kanter & Summers, 1994, p. 220) because performance of nonprofit organizations differs from that of private companies. Nonprofits define their success not around maximizing profits, like their business counterparts, but around their missions and the quality of their services that is notoriously difficult to measure due to its intangibility (Kanter & Summers, 1994; G. Saxton et al., 2014). And financial measurements, even together with nonfinancial measurements, are not sufficient to measure the accomplishments of nonprofit organizations. Kaplan thus proposed using a balanced scorecard to measure the performance of a nonprofit organization (Kaplan, 2001). Still, scholars have no consensus on the measurement of nonprofit performance (Carnochan et al., 2014). However, ratings or rankings of nonprofits from an independent agency such as Guider Star or Charity Navigator are commonly accepted and used as a proxy for measuring the performance of nonprofits (Gordon et al., 2009). Charity Navigator ranks nonprofit performance based on nonprofit organizations' financial health, accountability and transparency, and results reporting (Charity Navigator, n.d.). Four star nonprofits perform better than three star ones. Better performance of nonprofits usually results in future organizational success. Performance information, if incorporated in nonprofits' fundraising efforts, could motivate citizens to engage in philanthropic activities (Van Slyke, Ashley, & Johnson, 2007). This study now hypothesizes that:

H_4: Better organizational performance is more likely to increase donations to nonprofits than poorer organizational performance.

4.2.2 Type I and Type II donors

Using different standards to distinguish different donative motives creates complexity and difficulties. A list of well known and differing standards is as follows: *(1)* fast thinking (System 1) and slow thinking (System 2) (Kahneman, 2011); *(2)* intrinsic and extrinsic (Brewer & Brewer Jr., 2011); *(3)* emotional and rational (Kahneman, 2003; Loewenstein, 2000; Herbert A. Simon, 1955; Smith, 2003); *(4)* cause-driven and outcome-driven (Van de Ven & Engleman, 2004); and *(5)* self-centered (warm-glow) and altruistic (Andreoni, 1990; Rose-Ackerman, 1996). Clearly, *(1)* overlaps with *(3)* since System 2 inevitably involves rational thinking. And there are also overlaps between *(2)*, *(4)*, and *(5)* due to the fact that considering others' welfare in one's own decision is often more altruistic and but could be either cause-driven or outcome-driven and either intrinsic or extrinsic. Consensus is rare in terms of which way is the best to categorize different motives.

Based on four different dimensions of charitable giving – whether the object is tangible, whether it is located within, outside, or between individuals, who the actors are, and who the beneficiaries are, Bekkers and Wiepking (2010) documented eight motivational types of why donors give to nonprofits: (*a*) awareness of need; (*b*) solicitation; (*c*) costs and benefits; (*d*) altruism; (*e*) reputation; (*f*) psychological benefits; (*g*) values; and (*h*) efficacy. There are still, however, overlaps between certain motivational types, such as between *(a)* and *(g)*, because values (e.g. better world for children) promoted by nonprofits could increase donors' awareness of social needs (children need education, clean water, health care, and so on); between *(b)*, *(e)*, and *(f),* where donors could benefit psychologically because of being asked and/or being recognized publicly of their contributions; and between *(c)* and *(h)*, when an organization's efficacy is based on cost-benefit analyses. These overlaps demonstrate the difficulties of separating one motive another during the giving decision process; and in practice, scholars do indeed use different, overlapping standards when categorizing different types of motivations.

To simplify, this study focuses on two types of donors: Type I and Type II donors. The purpose of using Type I and Type II donors is that previous categorizations are not quite suitable for this study. The eight mechanisms developed by Bekkers and Wiepking (2010) do not focus on donors' motivations. Other categorizations, such as *(1)* to *(5)*, focus on donors' motivations but are single dimensioned. This study uses Type I and Type II donors not only to focus on donors' motivations but also to capture the overlaps between different motivations.

The way of labeling Type I and Type II donors is similar to the way of using system 1 and system 2 in Kahneman (2011). Kahneman (2011, p.13) described "mental life by the metaphor of two agents, called system 1 and system 2, which respectively produce fast and slow thinking…the features of intuitive and deliberate thought as if they were traits and dispositions of two characters in your mind." It should also be noted that Type I and Type II donors are far more complicated in reality. Here, Type I and Type II donors respectively represent self-centered cause-driven donors and altruistic outcome-driven donors. In general, Type I donors are more likely to be motivated by emotional stories and good causes, to enjoy warm-glow feelings about their giving decisions and actions, and to rely on system 1 to make decisions; while Type II donors are more likely to pay more attention to organizational outcomes and performance and make decisions using system 2.

These two types of donors respond differently to the same pieces of information about nonprofits. As modeled in Chapter 3, Type I donors are more likely to respond to cheap information; while Type II donors are more likely to respond to costly information.

Type I donors are more responsive to nonprofit missions that usually state the social needs that organizations try to satisfy. Type I donors gain utility from their charitable giving actions, including the feeling of being needed. Type II donors are more responsive to outcomes and performance of nonprofits and their utility usually depends on the utility of clients that these organizations serve. Therefore, treatment effects would differ across different types of donors. This study presents the following hypotheses:

$H_{1\text{-}1}$: When a more highly evaluated nonprofit mission is presented, Type I donors are more likely to donate than Type II donors.

$H_{2\text{-}1}$: When presented with simple requests, Type I donors are more likely to donate to nonprofits than Type II donors.

$H_{3\text{-}1}$: When higher program ratios are presented, Type II donors are more likely to donate to nonprofits than Type I donors.

$H_{4\text{-}1}$: When better organizational performance is presented, Type II donors are more likely to donate to nonprofits than Type I donors.

4.2.3 Conjoint experiment

This study employs an experimental design to test the proposed hypotheses. A conjoint experiment is thus used to causally identify the relative importance of different types of information and their influences on different types of donors. By using a conjoint experiment design, it complements the previous studies presented in Chapter 3 and Chapter 4 and allows triangulation of findings from different studies. Results from the conjoint analysis enhances the validity of the research and provides a better understanding of nonprofit information communication and its impacts on individual charitable giving decisions than either a qualitative or quantitative method alone.

Exploratory content analyses and descriptive statistics and regressions usually are unable to identify causalities of certain relationships. Lots of empirical studies employ survey data to draw correlations between certain mechanisms and giving decisions (e.g. Van Slyke and Brooks 2005; Wang and Ashcraft 2014). Van Slyke and Brooks (2005) used both interview transcriptions and survey data and found that participatory and voluntary experiences positively impacted charitable contributions to nonprofit organizations. Wang and Ashcraft (2014) also found that organizational commitment and involvement, in other words, voluntary experiences, positively influence people's giving to nonprofit organizations based on survey data. From these studies, it is still difficult to distinguish the impacts of self-interested motivations from impacts of pro-social altruisms on voluntary contributions. As mentioned above, different types of donors react to the same information differently. Voluntary contributions to NPOs might be motivated by self-interests such as reputation or good feelings or be motivated by altruism such as feeling social responsibility or sensing a civic duty of helping the needs (Bekkers & Wiepking, 2010; Brooks, 2002).

This study further incorporates experimental studies that help identify causal relationshipsbetween various types of information and donations to a nonprofit. Experimental methods, which allow researchers to identify causal mechanisms of certain relationships between variables, are being increasingly used in public administration and nonprofit management research, despite the fact that the total number of experimental studies remains relatively low (Kim et al., 2017; Li & Van Ryzin, 2017). Particularly, not many empirical studies of charitable giving motivations in public administration and nonprofit management use experimental methods (Bouwman & Grimmelikhuijsen, 2016;

Margetts, 2011). Economists, on the other hand, did many experiments to identify the motivations for charitable giving (see for example Andreoni & Payne, 2003; Andreoni & Rao, 2011; Gneezy & List, 2006; Karlan, List, & Shafir, 2011; Karlan & List, 2007; Landry, Lange, List, Price, & Rupp, 2006; List & Lucking-Reiley, 2002; List, 2008). In a typical economic analysis, a rational person responds to price changes based on the person's cost-benefit calculation. In this sense, if the price of giving decreases, people will be more likely to give. Increasing incomes (by changing the income elasticity), tax deduction, matching grants, seed money, and matching gifts can lower the giving price. A field experiment was employed to test whether "seed money" and refunds would increase charitable donations (List & Lucking-Reiley, 2002). The results showed that both seed money and refund had positive impacts on donations: increasing seed money from 10 percent to 67 percent of the campaign goal produced a nearly six-fold increase in contributions, with significant effects on both participation rates and average gift size. Imposing a refund increased contributions by a more modest 20 percent, with significant effects on average gift size. List and colleagues also conducted field experiments and found positively significant effects of matching grants and gifts on charitable giving (Karlan et al., 2011; Rondeau & List, 2008). For instance, Rondeau and List (2008) found evidence from both natural and laboratory experiments to illustrate the effectiveness of challenge gifts.

However, not many experimental studies about impacts of information on donation have been conducted, which implies that the causal mechanisms of impacts of information on donations are still unclear. This study tries to fill the gap between correlations and causalities by providing evidence from experiments. Among various experimental methods, conjoint experiments have been used in marketing research to determine customers' preferences over a set of alternative products (Curry, 1996) and have recently been applied to political science for choice-based research questions, such as voters' preferences of candidates (Hainmueller, Hopkins, & Yamamoto, 2014) and citizens' attitudes toward immigrants (Hainmueller, Hangartner, & Yamamoto, 2015; Hainmueller & Hopkins, 2015) and toward asylum seekers (Bansak, Hainmueller, & Hangartner, 2016). To causally identify the relative importance of multiple factors, which not only interact with each other but also influence respondents simultaneously, conjoint experiment is a cost-effective approach. Within a conjoint experiment, a respondent can answer multiple modules of paired questions. Thus, this increases statistical power and enables both within- and between-subjects analysis. In addition, donors' decision-making processes are similar to consumers' buying decisions (Hibbert & Home, 1997).

Using conjoint analysis meets the need of this study. As discussed, a nonprofit organization has various types of information in different forms that influence current and potential donors simultaneously. To effectively communicate with donors, nonprofits have to strategically deliver the right types of message to the right types of donors, as hypothesized in $H_{1\text{-}1}$ to $H_{4\text{-}1}$. In order to causally study the relative importance of various types of information to different donors, a research design must incorporate different traits of all these types of information while holding respondents' preferences stable and limiting the ordering effects. Traditional experimental designs usually randomly assign respondents into control and treatment groups, which generally result in a number of subgroups. Increasing numbers of traits to be studied will certainly boost the number of subgroups and increase the costs of conducting the experiment. Using traditional experimental design for this study is thus not cost-effective. Using a conjoint experiment, on the other hand, is an alternative to study many factors that contribute to decision-making at the same time in a much cheaper way (Bansak et al., 2016; Hainmueller et al., 2014). This study also demonstrates how experimental methods – conjoint experiments in particular – can be applied to nonprofit management studies.

4.3 Experimental design

This study used a conjoint experiment to investigate how various types of information about a nonprofit organization affect donors' giving decisions. The conjoint experiment was embedded in a survey that was conducted by Qualtrics in October 2016. Qualtrics, provided by the Qualtrics Company, is a research software and online platform that enables clients to collect data online (Qualtrics, n.d.). Though the main purpose of Qualtrics is for business, it is also widely used in academic research (Sue & Ritter, 2012). Qualtrics offers a service that customizes the sample of survey respondents to be representative of the U.S. population based on several socio-demographic criteria. This study used this Qualtrics service to survey 1,046 U.S. citizens. After excluding incomplete and unqualified answers (e.g., those who completed the survey within 2 minutes were excluded), the data resulted in 957 respondents (See Appendix C for descriptive statistics of socio-demographic variables). After removing missing values, the conjoint experiment yielded 8,632 observations. The Institutional Review Board of Rutgers University-Newark approved the survey. Informed consent was obtained from all the respondents by asking them to be consent to participate at the beginning of the survey (See survey questionnaire in Appendix D).

The conjoint experiment employed here is a standard fully randomized paired conjoint design (Bansak et al., 2016). The conjoint design asked respondents to first evaluate five pairs of nonprofit organizations that combine multiple randomly assigned attributes (types of information) side-by-side and then make donating decisions (See Table 4-1 for illustration). Among various conjoint and vignette designs, “the paired profiles conjoint design performs best in terms of reducing social desirability bias and replicating real-world behavior” (Bansak et al., 2016. Supplement, p. 4). Hainmueller et al. (2015) validated the effectiveness of the paired conjoint design. Their paired conjoint design generated the closest results to the real-world behavioral benchmark as compared to other vignette experimental designs.

Table 4-1: Exemplary pair of nonprofits in the conjoint experiment

	ATTRIBUTE	**Nonprofit 1**	**Nonprofit 2**
RANDOMIZATION	Mission	To inspire breakthroughs in the way the world treats children	To make the world better for children
	Message		Please help support our organization!
	Government funding	36%	64%
	Spending pattern	10% spent on administration	90% spent on programs
	Client characteristics	54% white, 60% male	54% black, 60% female
	Charity Navigator rating	☆ ☆ ☆ ☆	☆ ☆ ☆

If you had to choose, which nonprofit organization would you prefer to donate your money to ...

Nonprofit 1	**Nonprofit 2**
○	○

If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)

Nonprofit 1	
Nonprofit 2	
Total	

Within each pair, a profile of a nonprofit organization comprised of six randomized attributes, including organizational mission, direct requests for donations, government funding to organizational revenue ratio, spending pattern (administration/program ratio), Charity Navigator rating (stars), and gender and racial characteristics of clients served.

For designing mission-related information, this study first asked six volunteers to evaluate missions of the Topnonprofits 100 organizations from a 0 to 100 scale and then ranked them according to the average values of the six evaluated scores of a nonprofit mission. This study then selected and modified nonprofit missions from four organizations belong to two different NTEE major ten categories – the health nonprofit organization category (HE) and the international nonprofit organization category (IN) with a focus on children's affairs. Specifically, the Heart Association that aims at "building healthier lives free of cardiovascular diseases and stroke" and the Cancer Association that aims at "saving lives and diminishing suffering from cancer" belong to the HE category; the Inspiring Children that tries to inspire breakthroughs in the way the world treats children and the Better Children that tries to make the world better for children belong to the IN category. Missions of the Heart Association, the Cancer Association, the Inspire Children, and the Better Children organizations were adapted from missions of the American Heart Association, the American Cancer Society, the Save the Children, and the United Nations Children's Fund (UNICEF). The average evaluation scores of these four missions are 85.00, 91.67, 80.67, and 83.33, respectively. Table 4-2 lists all types of nonprofit information and values for each type of information.

Table 4-2: Conjoint attributes and attribute values

Attribute	Attribute Levels
Mission	Heart Association: Building healthier lives free of cardiovascular diseases and stroke Cancer Association: Saving lives and diminishing suffering from cancer Inspire Children: To inspire breakthroughs in the way the world treats children Better Children: To make the world better for children
Direct Request	(None) Please help support our organization! Thank you for your generosity!
Government Funding	0% 36% 64%
Spending Pattern	10% spent on administration 15% spent on administration 85% spent on programs 90% spent on programs
Client Characteristics	54% white, 60% male 54% black, 60% male 54% white, 60% female 54% black, 60% female
Charity Navigator Rating	☆ ☆ ☆ ☆ ☆ ☆ ☆

For research purposes of this study, only mission, direct requests, spending pattern, and Charity Navigator rating were analyzed. Based on the findings of big data analyses of tweets communicated between nonprofits and the public, these four types of information are most frequently communicated. The study included government funding ratio and clients' characteristics not only because they have been previously identified as important types of nonprofit information in the literature but also because more attributes could make paired nonprofits look like real organizations. However, mission, direct requests, spending pattern, and Charity Navigator rating are the foci of this study.

Each respondent was asked to evaluate five separate pairs of nonprofits and for each nonprofit organization, the values of all attributes were randomized. To avoid order effects, the order of attributes for each organization was also randomized. Table 4-1 displays an example of a pair of nonprofits randomly formed and presented to the respondents. After reviewing a pair of nonprofit profiles, respondents were first asked to choose the nonprofit organization they would prefer to donate to and then to allocate a hypothetical 100 dollars between the paired organizations. The first task resulted in a choice outcome variable coded as 1 for the preferred nonprofit and 0 for the other one in the pair. The second task generated a continuous variable that measures the amount of money out of 100 dollars donated to the preferred nonprofit.

This study identified the Average Marginal Component-specific Effects (*AMCEs*) of the randomized attributes of nonprofit information profiles. AMCEs (Hainmueller et al., 2014) measure the average causal effect of each attribute on respondents' support of a nonprofit. This study followed the estimate strategies developed by Hainmueller and colleagues (2014) and used linear least squares regression to regress the choice of a nonprofit and the allocation of 100 dollars between two nonprofits (rescaled into 0 to 1) on "sets of variables that capture the values of each attribute while omitting one level of each attribute as the reference category and clustering the standard errors by respondent" (Bansak et al., 2016, Supplement, p. 6).

The AMCEs can estimate the marginal effect of a particular attribute averaged over the joint distribution of the remaining attributes included in the regression model (see Bansak et al., 2016; Hainmueller et al., 2014; and Hainmueller et al., 2015 for detailed explanations). To illustrate, the following regression is used to estimate the AMCEs for the performance related information:

$$Choice_{ijk} = \alpha_0 + \beta_1\left(Rating_{ijk} = 4\, stars\right) + \varepsilon_{ijk}$$

where $Choice_{ijk}$ is the outcome variable measuring the choice between two pair nonprofits. Each respondent (indexed by $i \in \{1, 2, 3, \ldots, N\}$; N represents a random sample drawn from the population) is presented with *k* choice tasks, and in each of tasks which ask the respondent to choose from paired two nonprofits, the respondent chooses the most preferred of the *j* alternatives. The $Rating_{ijk}$ is a dummy variable coded 1 if the Charity Navigator rating for the organization is "4 $stars$"; and 0 if the Charity Navigator rating is "3 $stars$," which serves as the reference category. The AMCE of performance-related information (3 Charity Navigator stars mean lower organizational performance and 4 Charity Navigator stars mean higher organizational performance) on the probability of supporting choice can be understood as the result of the following hypothetical calculation: first, compute the probability of choosing a better performing nonprofit over an opposing nonprofit with a specific set of attributes; then compute the probability of choosing a poorer performing, but otherwise identical, nonprofit over the same opponent nonprofit, and take the difference between the probabilities for the better performing and the poorer performing nonprofit; then compute the same difference between a better performing and a poorer performing nonprofit, but with a different sets of attributes; finally, take the average of these differences over all possible combinations of the attributes according to their joint distribution. Thus, the ACME of performance-related information represents the average effect of performance-related information on the probability that the nonprofit will be chosen, where the average is defined over the distribution of the attributes across repeated samples.

The AMCEs are approporiate for this study because when donors make giving decisions, they usually are facing more than one type of organizational information, in other words, conditional information. One advantage of AMCEs, as noted by Hainmueller and colleagues (2014), is that it is defined as a function of the distribution of the treatment components, which also allows researchers "to explicity control the target of the inference by setting treatment components to be plausible or interesting" (p. 11). The AMCE thus makes explicitly that the treatment effect is conditional on the distribution of attributes, which is a situation that is quite similar to the real-world distribution and cannot be easily implemented in a classical survey expeirment where often only one or two treatments are manipulated due to the constraints of both scarce human resources and limited financial budgets. In addition, it is straightforward to interpret the change when a given attribute value is compared to the baseline.

4.4 Results

4.4.1 Main effects of information on donations

The effects of the organizational information attributes on the probability of nonprofit support and donations to nonprofits pooling across all respondents are plotted in Figure 4-1a and 4-1b (Results of the AMCE regressions are presented in Table 4-3).

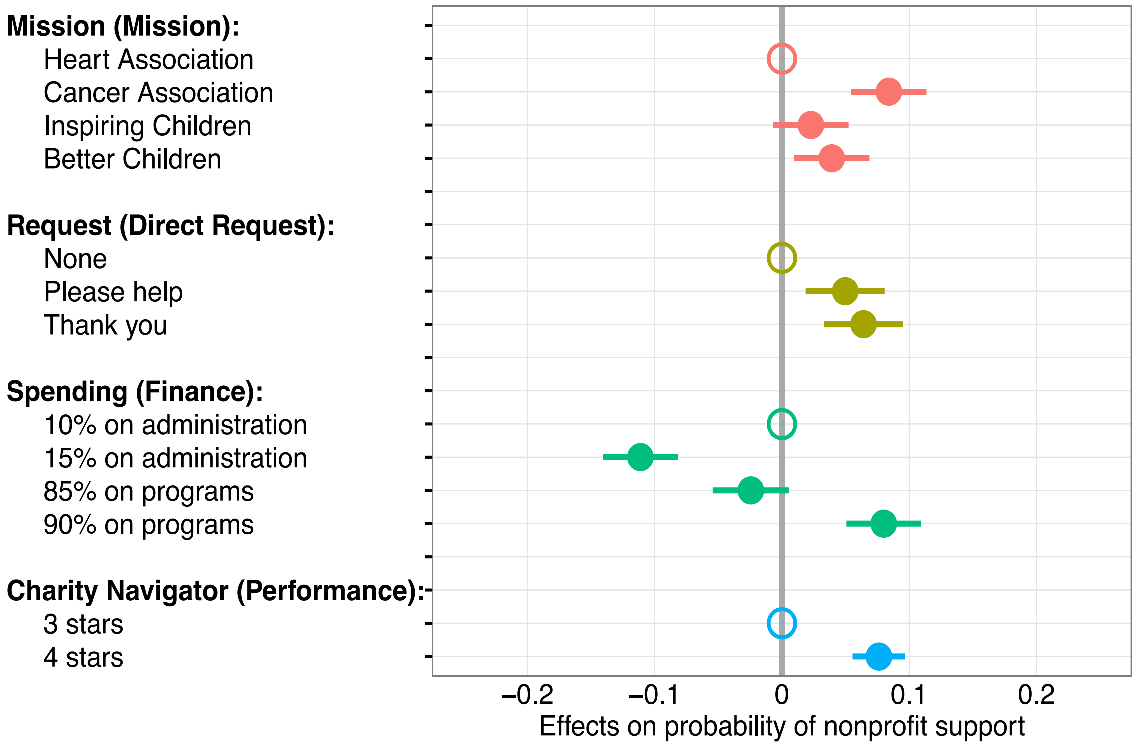


Figure 4-1a: Effects of nonprofit information on giving choices

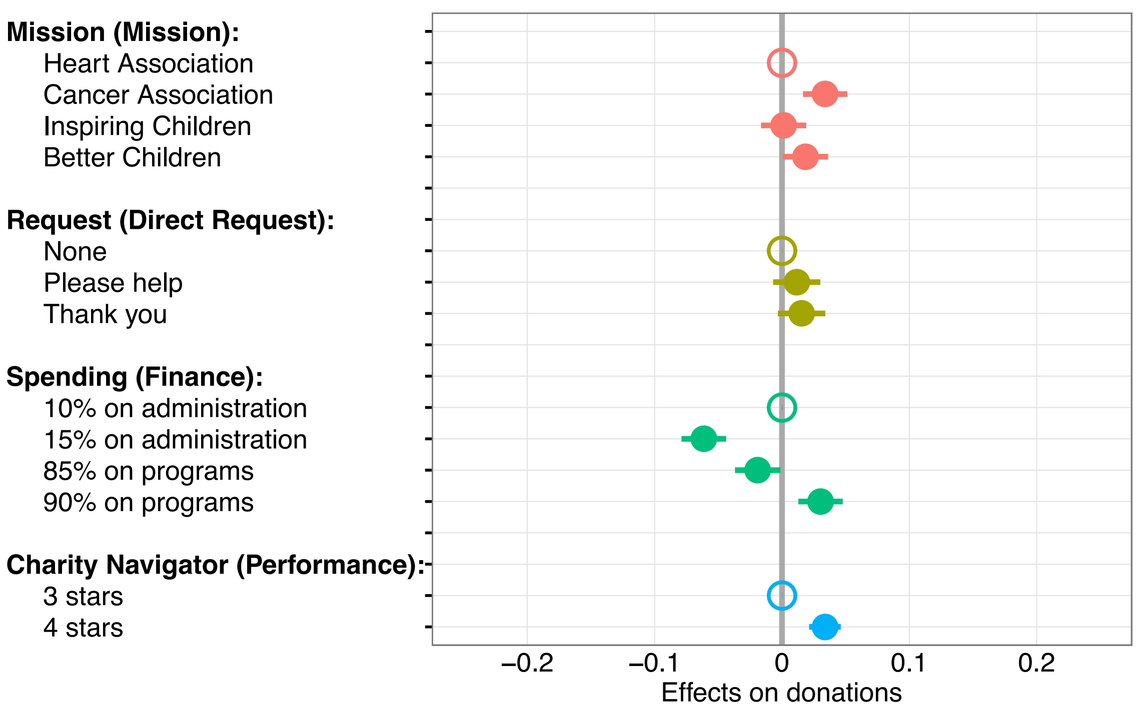


Figure 4-1b: Effects of nonprofit information on donations

The results show that donors do not treat all types of information equally and their preferences vary across attribute levels. Since effects of the organizational information attributes on the probability of nonprofit choices show a similar pattern of such effects on donations to nonprofits (see Figure 4-1), this study thus mainly focuses on analyzing the results of effects on giving choices. The results of effects on donations, following the same regression procedure used for estimating $Choice_{ijk}$, are discussed only if necessary.

Generally, in terms of the effect of mission-related information within a specific NTEE category, a nonprofit organization with a more highly evaluated mission is more likely to be chosen by current and potential donors (Table 4-3 Model 1). For example, compared to the Heart Association, the more highly evaluated Cancer Association is 8 percent more likely to be chosen by current and potential donors. That is also true if the same comparison was made between the Inspiring Children and the Better Children. However, the results are mixed if comparisons are made between organizations across different NTEE categories. The Better Children, which has a lower evaluation score (83.33) than the Heart Association (85.00), is 4 percent more likely to be chosen by respondents than the baseline. The similar advantage of a more highly evaluated mission disappears when the Inspiring Children, which also has a lower evaluation score (80.67) compared to the Heart Association. In other words, between-category effects can either be larger or smaller than within-category effects. Therefore, the results can only partially verify the H_1 by confirming the within-category effect, which is that donors are more likely to give to a more highly evaluated mission than a lower evaluated one, only if missions belong to a same NTEE category, in this study namely either the HE category or the IN (children affairs) category.

This study confirms that direct requests significantly increase donors' likeliness of giving to nonprofits. Simply asking "Please help support our organization!" significantly increases donors' giving probability by 5 percent; and saying "Thank you for your generosity!" increases the probability of donation even more, by 6.4 percent. Therefore, the results confirm the H_2 that direct requests are more likely to increase donations to nonprofits.

For effects of the spending pattern, which represents the financial information category, the results demonstrate a positive effect of higher program ratios and a strong negative effect of higher administration ratios on donations to nonprofits. Compared to the baseline of "10% spent on the administration", "15% spent on the administration" significantly lowers the probability of giving by 11 percent. On the other hand, "90% spent on programs", which is the positively framed side of the baseline, significantly increases the likelihood of giving by 8 percent. "85% spent on programs", which means a relatively higher administration ratio (15% spent on administration; or 5 percent more than the baseline), has a slightly non-significant negative effect on the giving choice (Table 4-3 Model 1) and a slightly significant negative effect on donations (Table 4-3 Model 4), where it decreases donations by 1.9 dollars versus the baseline information. There are two competing effects about the information of "85% spent on programs". The loss aversion effect of "85%", which means that "15% was spent on administration", an implication of 5% difference on administrative costs as comparing to the baseline, tends to decease donations. At the same time, the positive framing effect of "programs", as opposing to "administration", tends to increase donations. According to the results of Model 4, "5% difference on administrative costs" has a larger negative impact on donations than the impact of positively framing the message into “85% spent on programs”. The results thus confirm the *H_3* that higher program ratios are more likely to increase donations to nonprofits.

Nonprofits that deliver a piece of performance-related information indicating better performance – four star rated by Charity Navigator – are more likely to increase donations. Comparing to a three Charity Navigator star nonprofit, a four star organization increases giving probability significantly, by 7.6 percent (Table 4-3 Model 1) and donations by 3.4 dollars (Table 4-3 Model 4). The results confirm the H_4 that better performing nonprofits are more likely to attract more donations.

4.4.2 Effects of nonprofit information on Type I and Type II donors

As discussed in Section 4.2.2, this study focuses on the effects of nonprofit information on two different types of donors: Type I donors and Type II donors, which respectively represent cause-driven self-centered donors and outcome-driven altruistic donors. Therefore, to test $H_{1\text{-}1}$, $H_{2\text{-}1}$, $H_{3\text{-}1}$, and $H_{4\text{-}1}$, this study first asked respondents to rank four statements, in order to distinguish Type I donors from Type II donors. Before ranking four statements, respondents first read, “Please rank the following reasons for donating to charity. Use your cursor to reorder these reasons from most important (1) to the least important (4), as you see things. I donate because...”. Then respondents were presented the following statements:

(1) “It makes me feel good to help others”

(2) “I feel good about what the organization is doing”

(3) “I want my money to make a difference in society”

(4) “The charity is an effective organization”

If statement (1) “It makes me feel good to help others” or (2) “I feel good about what the organization is doing” was ranked at the first place, respondents were labeled as Type I donors, since these two statements describe self-centered feelings and cause related information, such as “to help others” and “what the organization is doing”. If statement (3) “I want my money to make a difference in society” or (4) “The charity is an effective organization” was the respondent’s first choice, the respondent was then categorized as a Type II donor. The reason for categorizing respondents who ranked higher the later two statements into Type II is that “to make a difference in society” is an altruistic and outcome related statement and “effective organization” is also an outcome related statement.

Do giving decisions vary across different types of donors? To test for interactions between donor types and the effects of the nonprofit information attributes, this study mainly analyzes the information’s effects by donors’ types. The informational effects by social-demographics of donors, such as gender, age, income level, education background, party affiliation, region, and marital status are not the foci of this study and are thus not reported. Figure 4-2a and Figure 4-2b show the results of the information effects on giving choices and donations by Type I and Type II donors, respectively. Overall, the information effects of the attributes are quite similar between the two different types of donors and are consistent with the effects on all respondents (Figure 4-1). Type I donors are not more likely to give than Type II donors when more highly evaluated nonprofit missions and direct requests for donations are presented (Table 4-3 Model 2 and Model 3); and Type II donors also do not respond more than Type I donors to higher program ratios and better organizational performance (Table 4-3 Model 5 and Model 6). In other words, this study cannot spot any significant difference between Type I and Type II donors in responding to these nonprofit information attributes.

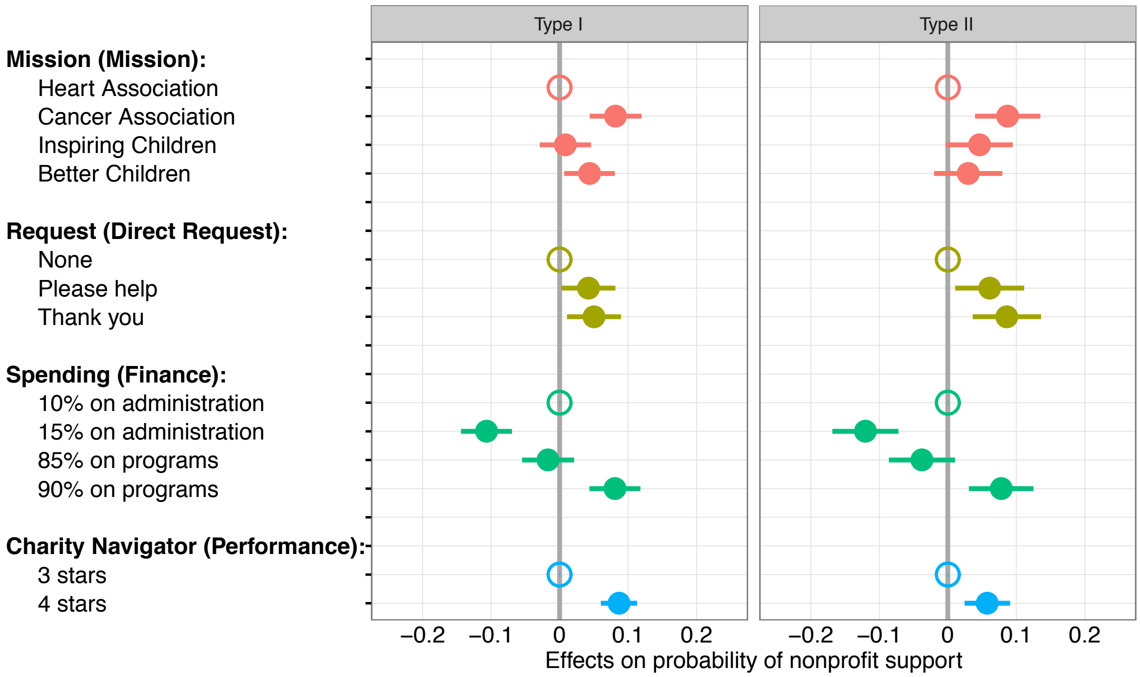


Figure 4-2a: Effects of nonprofit information on giving choices by Type I and II donors

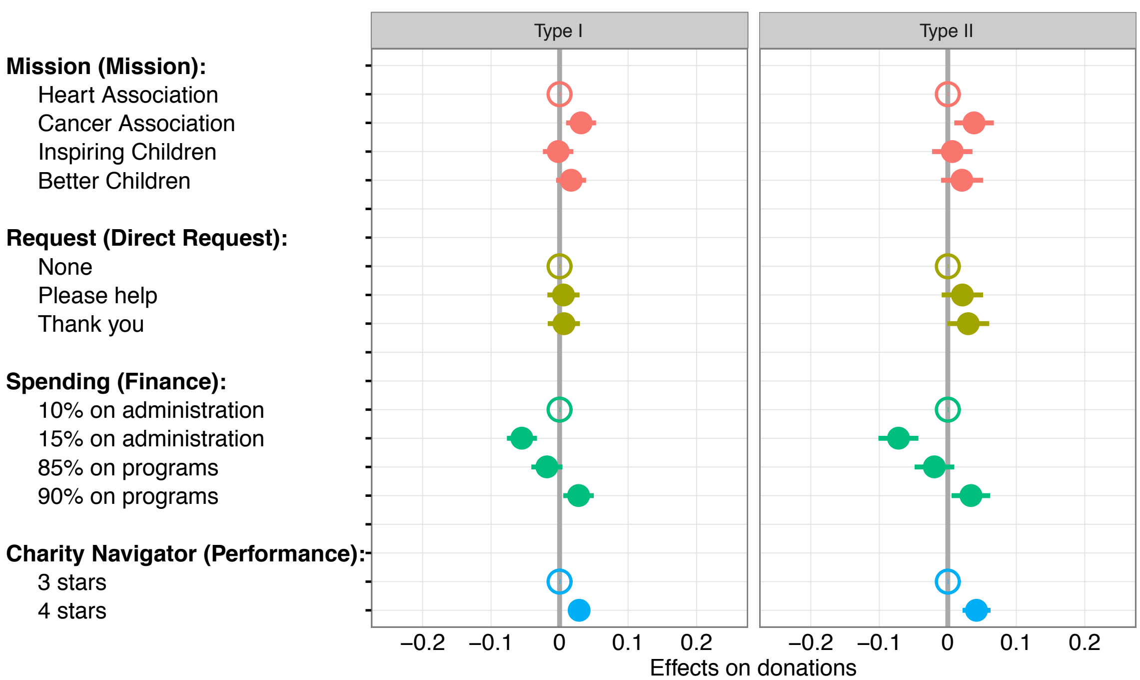


Figure 4-2b: Effects of nonprofit information on donations by Type I and II donors

Table 4-3: Pooled regression results of effects on nonprofit choices and donations

	Choices			*Donations*		
	(Model 1) All	(Model 2) Type I	(Model 3) Type II	(Model 4) All	(Model 5) Type I	(Model 6) Type II
Mission (Baseline: Heart Association)						
Cancer Association	0.084***	0.082***	0.087***	0.034***	0.031***	0.038***
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
Inspiring Children	0.023	0.008	0.046*	0.001	-0.002	0.007
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
Better Children	0.039***	0.044**	0.030	0.018**	0.017	0.021
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
Request (Baseline: None)						
Please help	0.050***	0.042**	0.061***	0.012	0.006	0.021*
	(0.013)	(0.016)	(0.021)	(0.008)	(0.010)	(0.013)
Thank you	0.064***	0.050***	0.086***	0.015**	0.006	0.030**
	(0.013)	(0.017)	(0.021)	(0.008)	(0.010)	(0.013)
Spending Pattern (Baseline: 10% on administration)						
15% on administration	-0.111***	-0.107***	-0.120***	-0.061***	-0.055***	-0.072***
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
85% on programs	-0.025	-0.017	-0.038	-0.019**	-0.019	-0.019
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
90% on programs	0.080***	0.081***	0.078***	0.030***	0.028**	0.034**
	(0.015)	(0.019)	(0.024)	(0.009)	(0.011)	(0.015)
Charity Navigator Rating (Baseline: 3 stars)						
4 stars	0.076***	0.087***	0.058***	0.034***	0.028***	0.042***
	(0.011)	(0.013)	(0.017)	(0.006)	(0.008)	(0.010)
Constant	0.403***	0.406***	0.400***	0.474***	0.483***	0.460***
	(0.017)	(0.021)	(0.027)	(0.010)	(0.013)	(0.017)
Observations	8,632	5,341	3,291	8,632	5,341	3,291
Adjusted R^2	0.030	0.030	0.031	0.018	0.013	0.023

Note: *p<0.1; **p<0.05; ***p<0.01

There is only one difference between the two types of donors due to the inconsistency of Type II donors' preferences between the two children's affairs organizations. On the one hand, Type II donors are more likely to give to the "Inspiring Children" than to give to the "Better Children". On the other hand, Type II donors surveyed allocated more money to the "Better Children" than the "Inspiring Children".

Type II donors are not consistent in making decisions of giving choices and monetary allocation. The results, again, are not statistically significant.

In sum, this study cannot confirm any of the H_{1-1}, H_{2-1}, H_{3-1}, and H_{4-1} and thus concludes that there is not significant difference between Type I and Type II donors in terms of their giving decisions responding to various types of nonprofit information. One possible explanation is that the effect of the ranking task is too weak to distinguish two types of donors. Although some donors ranked statement (1) "It makes me feel good to help others" or (2) "I feel good about what the organization is doing" higher than the other statements, the ranking might not be considered as a strong signal of a Type I donor. Another aspect of conjoint experiment design may also contribute to the insignificant difference between the two types of donors. When respondents were comparing a pair of nonprofits, they saw both cheap and costly organizational information. Presenting both types of information forced respondents to take an overall view of nonprofit information and, thus, might result in off set effects, which further caused the insignificant difference between Type I and Type II donors. Further understanding of different donors necessitates more research.

4.4.3 Effects of nonprofit information on donors with various giving experiences

Existing literature has identified a strong positive relationship between giving and volunteering experiences and donations (eg. Breeze, 2013). A recent study, however, found that previous giving and volunteering experiences from which individuals learned information about nonprofits significantly influenced individuals' volunteering decisions but not giving decisions (Li & McDougle, 2017). Therefore, this study also tests interactions between donors' giving and volunteering experiences and the effects of the nonprofit information attributes. Before being presented with the conjoint design, all respondents were asked questions regarding their experience of charitable giving and volunteering. Each respondent read "How often did you give money to a charity during the past 12 months?" and "How often did you do volunteer work for a charity during the past 12 months?" and then chose one answer out of six options (1) Not at all, (2) Once, (3) At least 2 or 3 times, (4) Once a month, (5) Once a week, and (6) More than once a week. To simplify the analysis, this study then dichotomized respondents' giving and volunteering frequencies to "Not at all" (coded as "0") or "Once or more" (coded as "1").

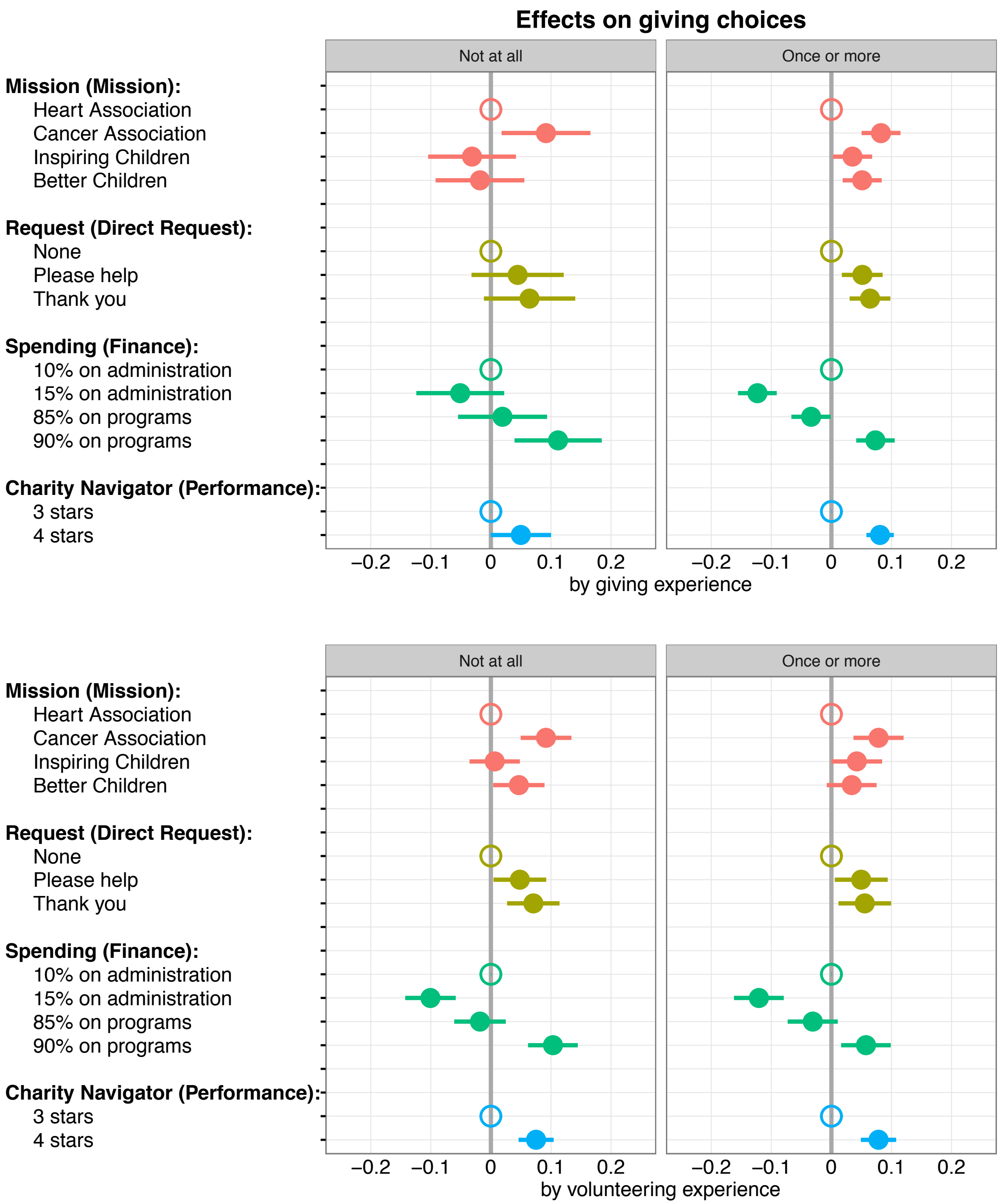


Figure 4-3: Effects on giving choices by giving and volunteering experience

How do giving decisions vary between respondents who did not give and volunteer and those who gave and volunteered? Figure 4-3 shows the results of the nonprofit information effects on giving choices by respondents who did not give and those who gave, and by those who did not volunteer and those who volunteered, respectively. Respondents who did not give made similar giving decisions to those who gave in responding to direct requests for donations and better Charity Navigator ratings (4 stars). The two groups, however, differed significantly from each other in terms of responding to missions related to children affairs and lower program ratios (85% spent on programs). Respondents without any giving records are less likely to give to the "Inspiring Children" by 3 percent and the "Better Children" by 2 percent, as opposed to the "Heart Association" (Table 4-4 Model 1). The results, though, are not significant. On the other hand, those who gave are significantly more likely to give to the "Inspiring Children" by 4 percent and the "Better Children" by 5 percent, as opposing to the baseline (Table 4-4 Model 2). In responding to the financial information about lower program ratios (85% spent on programs), compared to the baseline, those who never gave are slightly more likely to give, by 2 percent (Table 4-4 Model 1). Again, the result is not statistically significant.

Table 4-4: Regression results of effects on choices by giving and volunteering experience

	Giving choices					
	Giving frequency		Giving amount		Volunteering frequency	
	(1)	(2)	(3)	(4)	(5)	(6)
Mission (Baseline: Heart Association)						
Cancer Association	0.092**	0.083***	0.070***	0.103***	0.092***	0.078***
	(0.037)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
Inspiring Children	-0.031	0.035**	0.006	0.043*	0.006	0.042**
	(0.036)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
Better Children	-0.018	0.051***	0.015	0.069***	0.047**	0.034
	(0.036)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
Request (Baseline: None)						
Please help	0.044	0.051***	0.068***	0.031	0.048***	0.050***
	(0.032)	(0.014)	(0.018)	(0.019)	(0.018)	(0.018)
Thank you	0.064**	0.064***	0.088***	0.040**	0.071***	0.056***
	(0.032)	(0.014)	(0.018)	(0.019)	(0.018)	(0.018)
Spending Pattern (Baseline: 10% on administration)						
15% on administration	-0.051	-0.123***	-0.057***	-0.175***	-0.101***	-0.121***
	(0.037)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
85% on programs	0.019	-0.034**	0.030	-0.089***	-0.018	-0.031
	(0.037)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
90% on programs	0.112***	0.073***	0.104***	0.050**	0.103***	0.058***
	(0.037)	(0.016)	(0.020)	(0.022)	(0.021)	(0.021)
Charity Navigator Rating (Baseline: 3 stars)						
4 stars	0.050*	0.081***	0.065***	0.088***	0.075***	0.078***
	(0.026)	(0.012)	(0.014)	(0.016)	(0.015)	(0.015)
Constant	0.411***	0.401***	0.375***	0.432***	0.391***	0.413***
	(0.041)	(0.018)	(0.023)	(0.024)	(0.024)	(0.024)
Observations	1,438	7,174	4,693	3,939	4,304	4,318
Adjusted R^2	0.022	0.032	0.025	0.043	0.034	0.026

Note:*p<0.1; **p<0.05; ***p<0.01

Why do respondents who did not give act slightly differently from other groups? Is the deviation caused by the fact that the number in the subgroup of participants who never gave (1438) is much smaller than the subgroup of who gave in the past (7174)? Or is it because of the variations of the amount of dollars given to nonprofits between donors? This study tests the effects of information attributes on giving choices by dividing those who gave less (<=$100) and those who gave more (>$100) (see Table 4-4 Model 3 and Model 4). The results show that, after introducing two types of donors based on the amount of money they contributed to nonprofits and thus creating more balanced subgroups with 4639 observations in the "gave less" group and 3939 in the "gave more" group, the deviation of responding to missions disappears. Respondents who gave less are still more likely to give to the lower program ratios by 3 percent. But the results are insignificant.

Whether or not respondents have volunteering experience seems to not affect their responses to various information attributes (Figure 4-3), except to missions of the "Inspiring Children" and the "Better Children". Respondents without volunteering experience are more likely to give to the "Better Children" than the "Inspiring Children" while those who volunteered are on the opposite side (Table 4-4 Model 5 and Model 6). One possible explanation could be that all those who volunteered might have volunteered in organizations with missions that are quite similar with the mission of the "Inspiring Children" – to inspire breakthroughs in the way the world treats children.

4.5 Conclusion and Discussion

This study employed a conjoint experiment to research how nonprofit organizations can effectively communicate information to the public in order to increase donative revenues. This conjoint experimental design allows the randomization of various information attributes and thus allows for measuring the average causal effect of each attribute on respondents' giving choices of nonprofits. As discussed above, to effectively communicate nonprofit information with current and potential donors, an organization has to firstly decide what kinds of messages within each type of information that have to be delivered, and then has to deliver the right type of information to the right type of donors. The study shows that, generally, (1) donors are more likely to give to a more highly evaluated mission within a same NTEE category; (2) donors are more likely to give to a nonprofit if they are asked to; (3) donors are more likely to give to programs rather than administration and are more likely to give to higher program ratios than lower ones; and (4) donors are more likely to give nonprofits that perform better (here, represented by four star rating by the independent rating agency Charity Navigator.) In addition, there are neither significant differences between Type I and Type II donors, nor between donors with and without giving experience in the past, in terms of their giving decisions when responding to various information attributes.

The results have significant practical implications for nonprofits' communication strategies. It is uncommon and sometimes extremely difficult for nonprofit organizations to change their missions to be more highly evaluated. However, making simple direct requests, improving administrative efficiency to increase program ratios, and performing better to earn more stars from Charity Navigator are all achievable goals. For example, nonprofits will not bear a huge cost by increasing requests for donations, as making online requests for donations is virtually free. This study also confirms both the loss aversion effect and the positive priming effect, which suggest that even if a nonprofit has very low administrative costs, it is still better for the organization to report it as a high program ratio instead of a low administration ratio. In addition, the indifference between

Type I and Type II donors suggests that nonprofits might be better off to focus on overall communication effectiveness rather than to develop a communication strategy to target specific donors with customized information.

This study is among the first few to employ experimental methods to study nonprofit management, in particular to study the relationships between nonprofits' informational communications and donations. This study also introduces the conjoint experimental design to the nonprofit field. This method allows for testing causal effects of multiple attributes in a timely and cost-effective manner and has a much broader application in nonprofit management area than merely as showcased by this study. Using a conjoint experimental design is also a response to the recent call for more experiments in public administration and nonprofit management (Kim et al., 2017; Li & Van Ryzin, 2017; Mason, 2013).

The study is not without limitations. First, instead of measuring real donations made by individuals, the study only uses donors' giving choices and hypothetical dollars to measure donations, which do not address the gap between intentions and actions. Second, the fact that only two NTEE category organizations are included in the conjoint design certainly questions the external validity of the findings. Third, the ranking task to distinguish Type I and Type II donors employed in the study is probably too weak to be effective.

Future studies should fill the gap between giving intentions and donations by employing field experiments. To generalize the results, in particular, of the effects of more highly evaluated missions on giving decisions, researching more mission-related information across more NTEE categories is necessary in the future. Future studies that want to investigate the difference between Type I and Type II donors may have to develop a set of questions that can make a clear distinction between two types instead of ranking only four statements. This study provides answers to questions about the effects of nonprofit information on donations and at the same time brings in new questions about nonprofit information and donors' giving decisions that need to be addressed in the future. Hence, this study can serve as a call for further studies on nonprofit communications and it particularly invites more experimental studies in this field.

CHAPTER 5: CONCLUSIONS

This chapter summarizes findings of the big data analyses of tweets and the conjoint experiment, discusses the theoretical and practical implications, states the limitations, and suggests future research directions.

5.1 Summaries of Findings

This study is designed to better understand and help develop effective communication strategies, which are critical for tackling the challenge of increasing donations to nonprofits. This study uses various methods, including big data analyses, multivariable regressions, and a conjoint experiment, to investigate what types of information are communicated online between nonprofits and the public, why certain types of information are communicated more than other types of information, what the relationships are between frequencies of information communicated and the public attitude toward nonprofits, and how and why various information contents can influence individual donation decisions.

Based on big data analyses including word clouds and clusters of tweets, the study finds that mission-related information, direct requests for donations, financial information, and performance-related information are the main four types of information communicated between nonprofits and the public. The study also discovers that mission-related information and direct requests are more frequently communicated online than financial and performance-related information. This study then builds upon cheap talk games (Chakraborty & Harbaugh, 2010; Farrell, 1995; Farrell & Rabin, 1996) and warm-glow theory in charitable giving literature (Andreoni, 1990) to explain why such a communication pattern exists. This study provides a preliminarily explanation that cheap information (mission-related information and direct requests) is more frequently communicated because nonprofits assume that individuals who prefer online communication are more likely to be Type I donors, who are self-centered and cause-driven.

The study then employs multivariable regressions to test the effects of such communication by examining the relationships between frequencies of various types of information and public attitudes toward nonprofits. The study calculates the sentiment scores (Liu, 2015) based on tweets communicated between 100 nonprofits (Topnonprofits.com, 2015) and the public to measure public attitudes toward nonprofits. The public's attitudes toward nonprofits are strongly correlated with individual giving intentions (Webb et al., 2000). However, this study finds no significant relationships between frequencies of various types of information and positive attitudes toward nonprofits (higher sentiment scores).

If frequencies of information do not matter in attracting donations, do the contents of information matter? The study employs a conjoint experiment to investigate the influences of contents of information on donations. The conjoint experiment randomizes the attributes and levels of values of mission-related information, direct requests, financial information, and performance-related information, and surveys 1046 respondents from a representative national sample provided by Qualtrics (Qualtrics, n.d.). The results show that donors are generally more likely to donate when they are presented a more highly evaluated nonprofit mission (mission-related information), when they are asked by nonprofits (direct requests), when they are given higher program ratios of nonprofits (financial information), and when they are provided better performance indicators of nonprofits (performance-related information). Surprisingly, the self-centered cause-driven Type I donors make no significantly different giving decisions from the altruistic outcome-driven Type II donors when responding to the same pieces of information.

5.2 Theoretical and Practical Implications

First, the study demonstrates how new methods, such as big data analysis and conjoint experiment, can be employed to advance nonprofit management research. Text-mining methods of big data analysis, such as word clouds, clusters, and sentiment scores, are commonly used in computer science (Liu, 2015; Zhao, 2013), but are rarely seen in nonprofit research. Tons of data emerge online on a daily basis in this digital age. Big data provide great opportunities for scholars to research important questions of their own field, nonprofit management included. The study is among the first to use big data analysis methods in nonprofit management research. The results of big data analyses show that nonprofits use both cheap and costly information during communications with the public, but tweet cheap information more frequently. They could encourage more big data analyses in nonprofit studies and deepen our understanding of nonprofit management and help nonprofits to improve their financial health and performance.

The study also introduces a conjoint experiment to test the effects of various information contents on donors' decisions. Conjoint experiments have long been used by business administration studies, especially, marketing research, and have recently been employed by political scientists to investigate citizens' political attitudes toward politicians and immigrants (Bansak et al., 2016; Hainmueller et al., 2015). This study is probably the first work in public administration and nonprofit management to use such an experimental design. The cost effectiveness and flexibility in randomization of multiple attributes and levels of values within each attribute of conjoint experiments have great potential to be applied in public and nonprofit management studies, as showcased in this study.

The study contributes to the nonprofit management literature, charitable giving literature in particular, by examining the impact of nonprofit communication on donating decisions. Most of the existing literature about charitable giving deals with how donors' social demographic factors influence their donations (Wang & Graddy, 2008), or with donors' reactions to changing prices of giving through matching grants, seed money, challenging gifts, and other monetary arrangements (List & Lucking-Reiley, 2002; Rondeau & List, 2008), or to various soliciting means such as asking (Andreoni & Rao, 2011) and saying "thank you" (Karlan et al., 2011). Very little scholarly attention has been paid to the role that using communication strategies incorporating various forms of information can play in motivating donors to give to nonprofits. By providing new empirical evidence of the types of information communicated between nonprofits and the public, explaining why cheap information is communicated more frequently than costly information on Twitter between the two parties, and testing the relationships between communication frequencies of various types of information and the public attitude toward nonprofits, this study sheds new lights on nonprofit communication research, especially the relationships between various types of nonprofit information and donors' decisions.

Furthermore, instead of interviewing nonprofit managers about their organizations' strategies of using social media to provide perceptional attitudes, this study uses communicated information on Twitter to explore the reality of the use of information in communications between nonprofit and the public. The study also proposed a basic cheap information model that can be applied to other related nonprofit management issues, such as donors' use of traditional and novel information sources, nonprofits' strategies of communicating accountability and performance information with the public, and nonprofits' strategies of balancing economic and social values.

Additionally, the study deepens the understanding of nonprofit communication, especially online communication, by serving new empirical evidence of effects of various information contents. Existing literature has studied how nonprofits use different information channels to communicate with stakeholders to achieved desired organizational goals (Guo & Saxton, 2014; Lovejoy & Saxton, 2012; Lovejoy et al., 2012; Waters & Jamal, 2011) and how donors' reliance on information sources influences their giving decisions (Li & McDougle, 2017). However, the effects of frequencies and contents of communicated information on donors' decisions lack empirical evidence. This study provides empirical results and shows that the contents, rather than the frequencies, of information matter in increasing donations to nonprofits. In addition, the study shows that overall effects of more highly evaluated nonprofit missions, more direct requests, higher program ratios, and better performance indicators on donors' willingness to give are significant; but there is no significant difference between Type I and Type II donors in terms of responding to various information contents.

The study also has practical implications for nonprofit management, especially, nonprofit communications. As discussed, nonprofits communicate various types of information to the public for multiple purposes. Regarding communications for contributions, results of this study suggest that instead of paying more attention to communicating frequently with the public online, they should focus on the information contents they want to communicate. However, to communicate customized information to targeted donors may be not necessary, since there is no significant difference between Type I and Type II donors in responding to nonprofit information.

Ultimately, as the results from the conjoint experiment in this study indicated, nonprofits have to send out more direct requests for donations, increase program spending, and improve their performance, because donors are more willing to give to those organizations that request directly for donations, have higher program ratios and better performance indicators.

5.3 Limitations

The study is not without limitations. First, the tweets used for big data analyses were collected in a short time period in 2016. The short time period of tweets collection could bias the results because of being interrupted by “shocks” and not capturing the time variances. For example, during the presidential election in 2016, politicians, political organizations, and media also tweeted about fundraising and donations. These tweets could cause noises in analyses even after removing words related to political candidates. Also, it could be possible that, during this data-gathering period, nonprofits and the public tweeted more frequently about mission-related information and direct requests than financial and performance-related information. I data were collected from various years, the results might be different.

Second, the study only collected 6,000 tweets communicated between a nonprofit and its audience due to the free application limit set by Twitter. Only tweets from the past seven days are downloadable by the free applications developed by researchers. There is no rule of thumb on how many tweets should be used for big data analyses. However, more tweets would certainly improve the robustness of the study.

Third, the study only researched 100 nonprofit organizations (Topnonprofits, 2015). The relatively small number of nonprofits limits the generalizability of the study. Future studies should employ a more representative sample of 501(c)3 organizations. The 100 nonprofits were chosen because of their online visibility, especially their large number of Twitter followers, which allowed for collecting reasonably sufficient data for research in an effective way. If a nonprofit only had very a small number of followers on Twitter, it might take the two parties years to exchange 6,000 tweets, so it would be much more difficult to collect 6,000 tweets between such a nonprofit and the public. Nevertheless, results of the study cannot be applied to other circumstances without taking this limitation into consideration.

Another limitation is the indirect measure of donations in the regression models. The study used sentiment scores to measure public attitudes toward nonprofits. Even though positive public attitudes usually predict increases in donations (Webb, Green, & Brashear, 2000), indirect measures of donations cannot provide empirical evidence on relationships between frequencies of information and donations. The study can only provide evidence of no significant correlations between frequencies of information and public attitudes toward nonprofits.

The fourth limitation is that text-mining methods for big data analyses are not perfect. Clusters in this study only categorized the most frequently tweeted words; and sentiment scores were heavily reliant on the quality of machine learning of natural language. The lexicon (Liu, 2015) used for training the R program to compare words in tweets with and positive and negative words in the lexicon is widely accepted. However, the lexicon can be improved based on learning more tweets data. Furthermore, developing a specialized lexicon for nonprofit research is possible.

In the conjoint experiment, the study used giving choices and hypothetical dollars to measure donations, which did not fill the gap between intentions and actions. The study only tested the difference in effects of mission-related information between HE and IN organizations according to their NTEE categories. Including more NTEE category organizations would certainly improve the external validity of the results. In addition, in the conjoint design, the ranking task used to distinguish Type I donors from Type II donors might be too weak to be effective and the presence of both of the cheap and costly information might complicate the effects of nonprofit information on various types of donors.

5.4 Future Plans

This section suggests some future plans to overcome some of the shortcomings listed above. To enhance generalizability, future studies should expand the sample size from 100 501(c)3 organizations and collect more data (tweets) from longer time periods across multiple years. If the results were consistent with more data and across multiple years, it would definitely enhance the robustness of the study.

To deal with issues of the indirect measures of donations, future studies can combine the Twitter data with other data of nonprofits, such as financial information from their IRS 990 forms, where actual dollar amounts can be found and used as a direct measure. In addition, future studies can also employ field experiments by using actual dollars instead of the public's attitudes or giving intentions. Then, actual dollar amounts can be used to measure donations directly. To improve the quality of big data analyses, future plans include not only to collect more data but also to continue developing a suitable lexicon for future nonprofit management research.

In terms of the possible weak effect of ranking tasks to distinguish different types of donors, future studies can employ other tasks to achieve a stronger distinction effect such as presenting true cases involving choices between causes and outcomes and between self-centered and altruistic decisions. Other formats of survey experiments can also be used to test cheap information and costly information separately instead of combining them into a conjoint design. To test the effect of cheap information or costly information separately on different types of donors would advance our understanding of similarities and differences between Type I and Type II donors and help develop effective communication strategies. For example, using other tasks to distinguish different types of donors and only randomizing the contents of cheap information with fixed costly information would allow for testing the effect of cheap information on donors' decisions. In addition, as mentioned earlier, more field experiments could help address problems of indirect measurements of donations by using real dollars.

This study provides answers to questions about the effects of nonprofit information on donations and, at the same time, brings in new questions about nonprofit information and donors' giving decisions that need to be addressed in the future. Thus, this study serves as a call for more studies on nonprofit communications and invites more big data analyses and experimental studies in this field.

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Appendix A: Clusters of tweeted information

Please see: github.com/lihuafang/npo-online

Appendix B: Regressions of dichotomized dependent and independent variables

Table S3-1: Regressions of dichotomized dependent and independent variables

	Dependent variables:							
	Sentiment scores	**Dichotomized sentiment scores**						
	OLS	*logistic*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cheap info. (dummy)	1.645	0.069						
	(4.728)	(0.405)						
Cheap info.			0.005					
			(0.257)					
Mission				-0.047				
				(0.146)				
Request					0.060			
					(0.163)			
Costly info.						-0.005		
						(0.257)		
Finance							0.057	
							(0.403)	
Performance								-0.040
								(0.307)
Constant	72.286***	0.000	-0.004	0.400	-0.064	0.043	0.032	0.057
	(3.601)	(0.309)	(2.433)	(1.144)	(0.347)	(0.248)	(0.209)	(0.238)
Observations	100	100	100	100	100	100	100	100
R^2	0.001							
Log Likelihood		-69.280	-69.295	-69.243	-69.227	-69.295	-69.285	-69.286

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix C: Descriptive statistics of selected social-demographic variables

Table S4-1 Descriptive statistics of selected social-demographic variables

Variables	N	Mean	St. Dev.	Min	Max
Sex (Male=0, Female=1)	957	0.52	0.50	0	1
Age (18~29=0, 30~39=1, 40~49=2, 50~59=3, ≥60=4)	957	1.93	1.50	0	4
Race (Others=0, White=1, African Americans=2, Hispanic=3, Asian=4)	957	1.49	0.90	0	4
Education (Less than high school=1, High school graduate=2, Some college=3, 2 year degree=4, 4 year degree=5, Masters degree=6, Doctorate=7, Professional Degree=8)	957	3.96	1.53	1	8
Income (≤25000=1, 25000~49999=2, 50000~74999=3, 75000~99999=4, ≥100000=5)	957	3.09	1.47	1	5
Region (Northeast=1, Midwest=2, West=3, South=4)	957	2.28	1.12	1	4
Marriage (Married=1, Widowed=2, Divorced=3, Separated=4, Never married=5)	955	2.50	1.81	1	5
Giving frequency (Not at all=0, Once or more=1)	955	0.83	0.38	0	1
Donation (Amount of dollars)	957	649.48	1785.96	0.00	20000.00
Donation 1 (≤$100=0, >$100=1)	957	0.45	0.50	0	1
Volunteering frequency (Not at all=0, Once or more=1)	956	0.50	0.50	0	1

Appendix D: The Survey Questionnaire

Q000 This survey is being conducted by Qualtrics on behalf of researchers at Rutgers University. The survey will ask you about a variety of topics and the results will inform academic research and press releases.

Your participation is voluntary and your responses will be held confidential. As specified by the online research panel which invited you to participate in this survey, you will receive an incentive for your participation. We have tested the survey and found that, on average it takes around 10 to 15 minutes to complete. This time may vary depending on factors such as your Internet connection speed and the answers you give. To indicate that you consent to participate in this research, please click on the "Next" button below.

We care about the quality of our data. In order for us to get the most accurate measures of your opinions, it is important that you thoughtfully provide your best answers to each question in this survey.
Do you commit to thoughtfully provide your best answers to each question in this survey?

- I will provide my best answers (4)
- I will not provide my best answers (5)
- I can't promise either way (6)

If I will provide my best answers Is Not Selected, Then Skip To End of Block

Demo 1 We would like to start by asking you a few demographic questions.Which best describes your gender?

- Male (1)
- Female (2)

Demo 2 What is your current age?
If What is your current age? Is Less Than 18, Then Skip To End of Block

Demo3 What is your Race/Ethnicity

- White/Caucasian (1)
- Black/African American (2)
- Hispanic/Latino (3)
- Asian (4)
- Other (please specify) (5) ____________________

Demo4 Which of the following best describes your annual income before taxes?

- Less than $25,000 (1)
- $25,000-$49,999 (2)
- $50,000-$74,999 (3)
- $75,000-$99,999 (4)
- More than $100,000 (5)

Demo5 In which region of the United States do you currently reside?

- ❍ Northeast (1)
- ❍ Midwest (2)
- ❍ West (3)
- ❍ South (4)

q01 How often did you give money to a charity during the past 12 months?

- ❍ Not at all (1)
- ❍ Once (2)
- ❍ At least 2 or 3 times (3)
- ❍ Once a month (4)
- ❍ Once a week (5)
- ❍ More than once a week (6)

If Not at all Is Selected, Then Skip To How often did you do volunteer work for

q010 About how much in total did you give to charities during the past 12 months? (US dollars)

q02 How often did you do volunteer work for a charity during the past 12 months?

- ❍ Not at all (1)
- ❍ Once (2)
- ❍ At least 2 or 3 times (3)
- ❍ Once a month (4)
- ❍ Once a week (5)
- ❍ More than once a week (6)

q03 Please rank the following reasons for donating to charity. Use your cursor to reorder these reasons from most important (1) to the least important (4), as you see things . I donate because...

______ · It makes me feel good to help others (1)
______ · I want my money to make a difference in society (2)
______ · I feel good about what the organization is doing (3)
______ · The charity is an effective organization (4)

q11 On the next few pages, you will see five pairs of nonprofit organizations. For each pair of organizations, please indicate which one you would prefer to donate to.

q12 Nonprofit 1 Nonprofit 2
var attRaw = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var att = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var attributes = ["","","","","",""]; // Randomize the Order of Dimensions (avoid recency and primacy) for (i=0; i

q13 If you had to choose, which nonprofit organization would you prefer to donate your money to ...

- ❍ Nonprofit 1 (1)
- ❍ Nonprofit 2 (2)

q14 If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)

______ Nonprofit 1 (1)
______ Nonprofit 2 (2)

q21 Nonprofit 3 Nonprofit 4
// Read in Dimension Order from first module. Maintain this order across modules var str="${q://QID172493481/ChoiceTextEntryValue/13}"; var attributes=str.split(","); var attRaw = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var att = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var attributes = ["","","","","",""]; // Randomize the Order of Dimensions (avoid recency and primacy) for (i=0; i

q22 If you had to choose, which nonprofit organization would you prefer to donate your money to ...

- ❍ Nonprofit 3 (1)
- ❍ Nonprofit 4 (2)

q23 If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)

______ Nonprofit 3 (1)
______ Nonprofit 4 (2)

q31 Nonprofit 5 Nonprofit 6
// Read in Dimension Order from first module. Maintain this order across modules var str="${q://QID172493481/ChoiceTextEntryValue/13}"; var attributes=str.split(","); var attRaw = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var att = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var attributes = ["","","","","",""]; // Randomize the Order of Dimensions (avoid recency and primacy) for (i=0; i

q32 If you had to choose, which nonprofit organization would you prefer to donate your money to ...

- ❍ Nonprofit 5 (1)
- ❍ Nonprofit 6 (2)

q33 If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)
______ Nonprofit 5 (1)
______ Nonprofit 6 (2)

q41 Nonprofit 7 Nonprofit 8
// Read in Dimension Order from first module. Maintain this order across modules var str="${q://QID172493481/ChoiceTextEntryValue/13}"; var attributes=str.split(","); var attRaw = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var att = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var attributes = ["","","","","",""]; // Randomize the Order of Dimensions (avoid recency and primacy) for (i=0; i

q42 If you had to choose, which nonprofit organization would you prefer to donate your money to ...
- Nonprofit 7 (1)
- Nonprofit 8 (2)

q43 If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)
______ Nonprofit 7 (1)
______ Nonprofit 8 (2)

q51 Nonprofit 9 Nonprofit 10
// Read in Dimension Order from first module. Maintain this order across modules var str="${q://QID172493481/ChoiceTextEntryValue/13}"; var attributes=str.split(","); var attRaw = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var att = ["Mission","Charity Navigator rating","Government funding","Spending pattern","Client characteristics","Message"]; var attributes = ["","","","","",""]; // Randomize the Order of Dimensions (avoid recency and primacy) for (i=0; i

q52 If you had to choose, which nonprofit organization would you prefer to donate your money to ...
- Nonprofit 9 (1)
- Nonprofit 10 (2)

q53 If you had a budget of $100 to give, how would you allocate the money between these two organizations? (Type in any two numbers, as long as they add up to 100)
______ Nonprofit 9 (1)
______ Nonprofit 10 (2)

Q100 Finally, we have just a few last questions about you. Please recall that your responses are anonymous.

Demo 6 Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or what?

- Republican (1)
- Democrat (2)
- Independent (3)
- Something else (4)

Display This Question:
If 2012 ANES pid_lean Closer to the Republican Is Selected
Demo 6-1 Would you call yourself a strong Republican or a not very strong Republican?

- Strong Republican (1)
- Not very strong Republican (2)

Display This Question:
If 2012 ANES pid_lean Closer to the Democratic Is Selected
Demo 6-2 Would you call yourself a strong Democrat or a not very strong Democrat?

- Strong Democrat (1)
- Not very strong Democrat (2)

Display This Question:
If 2012 ANES pid_lean Neither Is Selected
Or 2012 ANES pid_lean Is Selected
Demo 6-3 Do you think of yourself as closer to the Republican Party or to the Democratic Party?

- Closer to the Republican (1)
- Closer to the Democratic (2)
- Neither (3)

Demo 7 What is the highest level of education you have completed?

- Less than high school (1)
- High school graduate/ GED (2)
- Some college (3)
- 2 year degree (4)
- 4 year degree (5)
- Masters degree (6)
- Doctorate (7)
- Professional Degree (JD, MD) (8)

Demo 8 Are you currently married, widowed, divorced, separated, or have you never been married?

- Married (1)
- Widowed (2)
- Divorced (3)
- Separated (4)
- Never married (5)

Demo 9 How many children under 16 years old, if any, live in your household?

- None (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 or more (5)

home Are you completing this survey at home or somewhere else?

- At home (1)
- Somewhere else (2)