

## ABSTRACT

Title of Document: ONLINE NETWORKS AND PROSOCIAL BEHAVIORS: EMPIRICAL STUDIES OF CHARITABLE DONATIONS AND ENVIRONMENTAL SUSTAINABILITY.

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My dissertation seeks to understand how online networks promote prosocial behaviors in creating social value. The first essay examines the use of Twitter on charitable giving behavior in online fundraising campaigns. Using a unique dataset from one of the first nonprofit organizations to conduct an online fundraising campaign via Twitter, the goal of this essay is to understand how social media and the interpersonal communications it facilitates influences donation outcomes. I find that generic content sent through a mass broadcast mode has a negative influence, whereas personalized content sent through a narrowcast mode has a positive influence on a focal agent's donation behavior. I further show that different types of persuasive content have varied impacts on outcomes. In the interpersonal context, content related to maintaining social relationships such as the visibility of other members' donations, the diversity of sources advocating action, and

strengthening interpersonal bonds, positively influence donation behavior, especially for those whose social ties with the charitable organization are weak. The second essay examines the design of online communities in supporting grassroots movements towards environmental sustainability. Using a dataset from one of the early pioneers of “green” online communities, the goal of this essay is to understand how online networks impact sustainable behaviors. Drawing from literature on observational learning and environmental sustainability, I show that a member’s total carbon savings is mainly influenced by the exposure to relevant others’ “green” behaviors. More specifically, a member’s decision to commit and perform a sustainable act is determined by the organizational structure and strength of relationships with fellow members. While organizing members into groups decreases individual’s environmental effectiveness in terms of total carbon savings, especially in larger groups, a higher frequency of communications among members increases sustainable behavior by enhancing interpersonal connections. Overall, the two studies provide important theoretical and practical implications for prosocial behaviors supported by online networks.

ONLINE NETWORKS AND PROSOCIAL BEHAVIORS: EMPIRICAL  
STUDIES OF CHARITABLE DONATIONS AND ENVIRONMENTAL  
SUSTAINABILITY

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## Chapter 1: Introduction and Overview

*"We cannot live only for ourselves. A thousand fibers connect us with our fellow men; and among those fibers, as sympathetic threads, our actions run as causes, and they come back to us as effects."*

- Herman Melville, *Moby Dick*

*"For that which is common to the greatest number has the least care bestowed upon it. Every one thinks chiefly of his own, hardly at all of the common interest; and only when he is himself concerned as an individual. For besides other considerations, everybody is more inclined to neglect the duty which he expects another to fulfill; as in families many attendants are often less useful than a few. Each citizen will have a thousand sons who will not be his sons individually but anybody will be equally the son of anybody, and will therefore be neglected by all alike."*

- From Aristotle's *"Politics"*, written c.a. 350 BC

Advances in information technologies are rapidly changing human connections and perhaps even the world. Whether the increased connectedness will unite people to achieve greater social good or disperse individuals to pursue their own self-interests remains a key question. For instance, the pervasiveness of social media use creates a "networked public sphere"<sup>1</sup>, in which individuals come quickly and in large numbers to discuss and organize towards collective action. The success of overthrowing dictators in the Arab Spring revolutions demonstrates the efficacy of the networked sphere in implementing social change. However, increased participation by the masses also implies a decreased effort at the individual level. The resulting "slacktivism"<sup>2</sup>, which refers to activities having no real impact, is evidenced by the Occupy Wall Street movement in 2011. Thus, the new era of social activism raises hopes as well as questions about personal accountability in addressing social dilemmas.

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<sup>1</sup> Benkler, Y. (2006). *The Wealth of Networks: How Social Production Transforms Markets and Freedom*, Newhaven: Yale University Press.

<sup>2</sup> Christensen, H. C. "Political activities on the Internet: Slacktivism or political participation by other means?", *First Monday*, 16,2.

When asked to contribute to a public good (i.e. charitable giving) or refrain from consuming a common good (i.e. air pollution)<sup>3</sup>, a rational individual, according to economic theory, should always reject such requests and “free ride<sup>4</sup>” in order to maximize her utility (Isaac and Walker 1988). Yet people commonly engage in activities that seem to be against their best interest – they volunteer, give money to charitable organizations, donate blood, and even sacrifice their life for strangers. Such actions intended to benefit one or more people, often at a cost to oneself, are known as *prosocial behaviors* (Batson 1998). Understanding the decision making process for prosocial behaviors differs from the traditional model of “rational” behaviors, in which an agent transfers her resources (i.e. money or time), in exchange for products or services. Prosocial decision making involves an individual transferring her resources to another entity (i.e. individual, organization, etc.) without expecting any explicit return. Prior research has offered an alternative explanation of rationality by incorporating the utility of others or *other-regarding preferences* (Benabout and Tirole 2006) into utility calculation, and suggests that a broad set of motives shape prosocial behaviors. For instance, many individuals engage in prosocial behaviors to obtain psychological rewards such as altruism or “warm-glow” (Andreoni 1990), or social rewards such as reputation (Fehr and Schmidt 1999; Bolton and Ockenfels 2000). Alternatively, people act prosocially to maintain social relationships with other members based on reciprocity (Trivers, 1971) or social identity (Tajfel and Turner 1985).

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<sup>3</sup> Brewer and Kramer (1988) make a distinction between the provision of public goods and commons dilemmas as examples of social dilemma, but the outcome for individuals is the same; that is, utility decreases.

<sup>4</sup> Here, I use “free riding” to describe the strategic behavior of an individual to accept the benefits of a collective action without making a positive contribution such as enjoying fresher air from a reduction in pollution.

The inherent challenge of assigning value to implicit rewards necessitates that individuals seek information externally to gauge whether undertaking prosocial behavior is worthwhile. Unlike products or services whose value can be captured in terms of price, there is no market to determine the price of a prosocial act. Thus, social information about others' behaviors can serve individuals as important factors in evaluating the potential outcome against their own preferences. For instance, experimental studies have shown that preserving the anonymity of subjects reduces individual contribution (Andreoni and Petrie 2004), whereas observing the punishment of free riding individuals increases cooperative behavior (Fehr and Gächter 2001). While findings from prior lab experiments suggest that information influences individuals' prosocial behavior, there is a gap in the literature on how technology facilitates the flow of information about others' behaviors to act prosocially in field settings, especially in an online context. In addition, the measurable and symbolic actions of others, such as the actual amount of a donation and words of support, respectively, can serve as different types of influence on individuals' behaviors.

My dissertation seeks to address this gap by conducting empirical studies in two different online contexts. The Internet and Web 2.0 technologies have been instrumental during the past decade in creating opportunities for people to contribute towards greater social good. Enabled by information technology (IT), people are providing the impoverished with microloans (e.g. Kiva.org), giving money to support nonprofit causes (e.g.: FirstGiving.org), and voicing their concerns over public issues through social media platforms such as Facebook and Twitter. While performing these activities is nothing new, the participants are no longer from the same town or neighborhood and are

increasingly total strangers from geographically disconnected locations. As more social interactions move from offline to online, the Internet presents an interesting research setting.

In addition, the visibility of information about individuals and their actions on the Internet helps people to (1) coordinate and publicize new digital content, and (2) to allow communities to support activities through disseminating information, financial contribution, and moral encouragement. Better understanding of how information influences prosocial behavior will help inform not only the optimal design of incentives for individuals but also design policies to support communities. I present two essays that examine prosocial behavior in two different online contexts.

The first essay examines the use of a micro-blogging platform to solicit donations from online networks. Unlike the traditional method of large organizations soliciting charitable donations through direct mail or field petitions, often for major disaster relief, the Internet enables social entrepreneurs and small nonprofit organizations to fundraise small amounts from individuals who might otherwise be difficult or costly to reach. Because information flows rapidly through networks of friends and strangers, organizations must consider how to promote a cause effectively.

Using a unique dataset from one of the first nonprofit organizations to conduct an online fundraising campaign via Twitter, the goal of this essay is to understand how social media and the interpersonal communications it facilitates influences donation outcomes. Drawing from literature on the role of information on charitable giving (Andreoni 2006; Soetevent 2005), I show that the donation decision of a focal actor is mainly influenced by the strength of the relationship between the focal actor and the

source, the types of content received, and the interaction between the two. In addition, I show that the information about how a message was broadcast has a different impact on members as compared to nonmembers<sup>5</sup>. While generic content sent through a mass broadcast mode has a negative influence, personalized content sent through a narrowcast mode has a positive influence on a focal agent's donation behavior. I further show that different types of persuasive content influence an individual's donation decision. Lastly, I consider how the characteristics of users on social networks interact with the message content to determine the donation outcome.

The second essay examines the effect of online communities on prosocial behaviors in an environmental sustainability context. Unlike traditional grassroots efforts to save the environment such as programs to increase recycling in suburban neighborhoods (Cialdini et al. 1990), the Internet enables a larger number of people from geographically disconnected locations to participate, thereby increasing the potential for social impact. Observing the behavior of those with similar interests can create a collective atmosphere that strengthens individuals' motives to participate.

Using a dataset from one of the early pioneers of "green" online communities, the goal of this essay is to understand how online networks impact sustainable behaviors. Drawing from literature on observational learning and environmental sustainability, I show that a member's total carbon savings is mainly influenced by the exposure to relevant others' "green" behaviors. More specifically, a member's decision to commit and perform a sustainable act is determined by the organizational structure and strength of relationships with fellow members. While organizing members into groups decreases

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<sup>5</sup> Here, I define member as a person who has a direct social tie to the firm, whereas a nonmember is not directly connected to the firm but rather through another member. The later section describes these terms in more detail.

carbon savings, especially in larger groups, a higher frequency of communication among members to enhance interpersonal connections increases sustainable behavior. In addition, I show the moderating effect of groups on total carbon savings.

The following chapters provide more details on these two studies, discuss the preliminary findings, and outline future research directions. The findings from my dissertation will inform policy makers in nonprofit organizations and government organizations on how IT can create social value and foster prosocial behavior in online communities.

## Chapter 2: Tweeting for Good: An Empirical Investigation of Micro-Blogging and Prosocial Behavior

### Abstract

Firms are increasingly leveraging social media to engage customers and increase revenue. Using charitable giving as a research context, I demonstrate the value of information technologies in extracting, analyzing, and assessing the impact of social media on donations. Using detailed communication data on a Twitter fundraising campaign, I show that the donation decision of a focal actor is mainly influenced by the strength of the relationship between the focal actor and the source, the types of content received, and the interaction between the two constructs. In addition, I show that information about how a message was broadcast has a different impact on members than nonmembers. While generic content sent in a mass broadcast mode has a negative influence, personalized content sent in a narrowcast mode has a positive influence on a focal agent's donation behavior. I further show that different types of persuasive content influence an individual's donation decision. Types of content providing information that aids a focal agent to make a donation decision in *private* frame such as a matching donation from a sponsor or requests to perform a small task, do not lead to increased donation behavior. On the other hand, types of content relevant for *interpersonal* frame, such as the visibility of other members' donations, the diversity of sources advocating action, and strengthening interpersonal bonds, positively influence donation behavior. Lastly, I consider how the characteristics of users on social networks interact with message content to determine donation outcome. This study is among the first to empirically examine how social media influences charitable behaviors in the online context.

## 2.1 Introduction

Online social networks services such as Facebook and Twitter are changing the way we communicate and socialize with others. This phenomenon is transforming how firms engage with their customers. In particular, firms using social media platforms for marketing their products and services are increasing rapidly. According to a 2011 Pew Internet & American Life Project study, the majority of adults in America who are online use social networking sites.<sup>6</sup> Combined with a 2011 Nielsen study's findings that 92 percent of online consumers trust recommendations by friends, family, and word of mouth above all other forms of advertising and 70 percent of consumers trust online consumer reviews by people they don't know<sup>7</sup>, it is no surprise that firms are striving to better understand their social media constituents and form deeper connections with them.

As consumers are influenced by interpersonal communications, or online word of mouth (Giese et al. 1996, Rist 2005), there is reason to believe that firms can proactively manage word of mouth (WOM) to influence a meaningful outcome. Prior research has shown empirical evidence on the relationship between online WOM (i.e. product reviews and movie recommendations) and firm outcomes such as sales and product adoption (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004; Liu 2006; Sonnier, McAlister, and Rutz 2011). Other research has focused on firm-generated WOM where firms use various tactics to encourage consumers to spread information in viral marketing campaigns. One interesting study by Godes and Mayzlin (2009) has shown that less loyal

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<sup>6</sup> Madden, Mary and Zickuhr, "65% of Online Adults Use Social Networking Sites", Pew Internet & American Life Project, August 26, 2011. Accessed on March 23, 2012, <http://pewinternet.org/Reports/2011/Social-Networking-Sites/Overview.aspx>

<sup>7</sup> Nielsen, "Global Consumers' Trust in 'Earned' Advertising Grows in Importance", April 10, 2012.



customers are effective in terms of transmitting WOM that drives sales, while opinion leaders are important only among loyal customers, suggesting that firms need to focus more on customers who were previously thought unimportant in their marketing strategy. In addition, firms can identify the types of products that are most often talked about when monitoring WOM to drive sales (Berger and Schwartz 2011; Netzer et al. 2012), made possible by availability of data and real-time analytics on online social conversations.

While these studies suggest that firms can identify the types of customers and the topics of conversations in online WOM, the question of what the firms should do to influence consumers to make purchases has not been fully answered. For instance, underlying social networks determine who and how many people receive firm initiated WOM communications. Whether consumers comply with a firm's attempt to influence them, however, is a function of who transmitted the message, the quality of the message being transmitted, and the level of interest or involvement consumers have with the firm (Perloff 2010). What communication strategy should firms use for loyal customers vs. less loyal customers? What information should firms include to increase customer engagement? How do social networks facilitate online WOM and impact customer decisions?

To answer these questions, I collected data on an online charitable giving campaign on Twitter with the cooperation of a 501(c) nonprofit organization, whose identity is kept confidential. Nonprofit organizations and social entrepreneurs have embraced social media technologies to engage with their constituents. As a result, online charitable

donations have experienced rapid growth (over 55 percent annually in the past decade<sup>8</sup>), partly due to the recent development of Internet and Web 2.0 technologies greatly reducing the costs of promoting and soliciting charitable donations. More importantly, information technology changed charitable giving from what was a private decision to an interpersonal decision. For instance, Fowler and Christakis (2010) found that social networks inspire greater generosity, where subjects in lab experiments were "influenced by fellow group members' behavior in [their] future interactions with others who were not a party to the initial interaction." In other words, people become more generous when others are involved. Charitable giving is one example of prosocial behavior, or doing "good" to benefit others or society. While several experimental studies offer insights on how information about others affect prosocial behavior in an offline context (Andreoni and Payne 2003; Benabou and Tirole 2006; Jacobsen and Petrie 2008), there is a lack of empirical evidence in the online context, with the exception of Rhue and Sundarajan (2010). Given that interpersonal communications mediated by social networks are observable and measurable, online charitable giving is a useful research setting to investigate the effect of communication patterns and content on customer decisions.

In this campaign, two types of people were solicited to donate on Twitter: members, a set who are directly connected to the nonprofit organization (i.e. firm) by subscribing to the organization's Twitter profile (i.e. follower), and nonmembers, a set who are indirectly connected to the nonprofit organization through another set of people (i.e. follower-of-follower, follower-of-follower-of-follower, etc.). For instance, firms have a closer relationship with existing members than nonmembers, exerting a different level of

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<sup>8</sup> A study conducted by Network For Good reports \$381 million in 2009, and the trend is continuing (<http://www1.networkforgood.org/online-giving-study-donations-driven-donor-experience-year-end-gifts-and-large-scale-disasters>), accessed on June 30, 2001

influence on their subsequent behaviors (Godes and Mayzlin 2009). Each type received one or more tweets, firm as well as user-generated content (UGC) consisting of no more than 140 characters, that contain (a) the source or content creator's information, (b) a message, with varying degrees of persuasive content to promote or donate to a campaign, and (c) whether a message was delivered to other followers (i.e. *mass broadcast*), or directed to a specific person (i.e. *narrowcast*)<sup>9</sup>.

These communication features embedded in a tweet constitute different levels of persuasiveness to the recipients (Perloff 2010). There is extensive empirical literature on persuasive communication, and a detailed review of this work is beyond the scope of this study. According to Perloff, prior research on persuasion has examined three classes of determinants relevant for this study: (a) source perception such as credibility, (b) message characteristics such as argument quality, and (c) recipient characteristics, such as involvement, personal relevance, and motivation. These variables enhance the likelihood of recipients not only processing message content but also changing their behavior. For instance, content creators use different compliance gaining strategies to persuade recipients to agree to target behaviors, whether informing others about the campaign or donating. Some of these tactics include *foot-in-the-door* (FITD) or increasing the recipient's commitment to the cause by performing a low level task, offering gifts, or sponsor matching to reduce the costs of donation. Another set of tactics attempts to build a closer relationship with the recipients such as enhancing the source's likeability by writing thank you notes. The implications for the two types of communication strategies are that the content will be more generic, pertaining to multiple recipients, in the mass

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<sup>9</sup> In Twitter, a tweet is sent to all followers by default, unless the sender chooses to target a specific person by invoking a "@" symbol, followed by the person's Twitter ID, at the start of a tweet.

broadcast mode of communication, whereas content will be more personalized in the latter (Mangold and Faulds 2009). More formally, I address the following research questions:

- How does the communication mode in a micro-blogging platform, such as mass broadcast versus narrowcast, affect a focal individual's prosocial behavior?
- How does a focal actor's relationship to the firm (i.e. member vs. nonmember) influence her prosocial behavior?
- How does persuasive content (i.e. observing the donations of others, FITD, etc.) affect a focal individual's prosocial behavior?

Using detailed communication data soliciting charitable donations on Twitter, I show that the donation decision of a focal actor is mainly influenced by the strength of the relationship between the focal actor and the source, the types of content received, and the interaction between the two constructs. First, information about how a message was broadcast has a different impact on the members than nonmembers. While generic content sent in the mass broadcast mode has a negative influence, personalized content sent in narrowcast mode has positive influence on a focal agent's donation behavior. This is an important result and is in contrast to previous work that demonstrated that WOM can drive important outcomes (Chevalier and Mayzlin 2006). That is, while WOM is effective in recruiting more people to spread information, developing personal relationships results in a more profitable outcome.

I further show that different types of persuasive content matter in influencing an individual's donation decision. Types of content providing information that aids a focal

agent to make a donation decision in *private* frame, such as a matching donation from a sponsor or requests to perform a small task, does not lead to increased donation behavior. On the other hand, types of content relevant for *interpersonal* frame, such as the visibility of other members' donation, the diversity of sources advocating action, and strengthening interpersonal bonds, positively influences donation behavior. Lastly, I consider how the characteristics of users on social networks interact with message content to determine donation outcome. While many studies have examined charitable giving behavior in lab settings or simulations (for reviews, see Andreoni (2006)), this study is among the first to empirically examine how social media influences charitable behaviors in the online context.

In addition, I also make a methodological contribution, demonstrating the use of business analytics in extracting and analyzing Twitter data. With the increasing availability of digitized data sources creating difficulty in tracking and quantifying information from data, I use text analytics and social network analytics to analyze the data (Chen et al. 2012). Text analytics has its roots in computer science, and it addresses the challenges inherent in analyzing user-generated content (Godes et al. 2005). Social network analytics identifies important people and their influence on others. Together, these techniques can help firms to not only find people of importance but also to understand what categories of content would likely influence them to the target behavior.

The rest of the paper is organized as follows. Section 2 presents the theoretical motivation and review of relevant literature. Section 3 describes the research context. Section 4 presents the data analyses and results. The paper concludes with a discussion of the results and suggestions for future research in this area.

## **2.2 Literature Review**

I review relevant literature on two streams of thought to address how social media influence an individual's decision making process to donate to a charitable organization. The first focuses on how social networks influence dissemination of content to individuals, and the second relates to how different types of persuasive information convey in interpersonal communication affects charitable giving behavior. I draw upon these streams of research to set up a theoretical framework to analyze how the dissemination of information through online social networks affects the donation decisions of a focal actor.

### **2.2.1 Social Networks and Interpersonal Communication**

The first stream of research explores how social networks facilitate and influence individuals in the exchanging and processing of information. The emergence of social media platforms such as Facebook and Twitter has drastically increased the scale and speed at which users create and disseminate content through word-of-mouth (WOM), which is a well-established construct (Arndt 1967) that has a significant impact on consumers' actions, preferences, and choices (Chevalier and Mayzlin 2006). Consumers sharing their opinions about a product or service have become a valuable resource for organizations striving to raise consumer awareness (Liu 2006). As a result, firms have changed their strategies for communicating with customers (Mangold and Faulds 2009). For instance, nonprofit organizations have embraced social media to interact with volunteers and donors, to educate potential new members about their programs and services, and to develop deeper relationships with their constituents (Waters 2009).

How social networks enhance the effectiveness of WOM has been demonstrated in several empirical studies. Online social networks expose new, more valuable information through interpersonal connections, in which a social tie serves as a conduit for information, thereby either reducing search costs or enabling the gathering of diverse information from different parts of the network (Granvoetter 1973; Kaplan and Henlein 2010). In addition, online connections can exert influence on others' behaviors, which has been demonstrated in various contexts such as smoking, obesity, happiness, and other types of behaviors and states (Christakis and Fowler 2007, 2008; Lin et al. 2009; Singh 2005; Cacioppo et al. 2009).

However, as information travels further along a chain of links in the social network, the likelihood of social influence on individual behavior depends on the nature of relationships in a pair of two nodes in the network such as mutuality of friendships or acquaintance (Christakis and Fowler 2007), as well as "degree of influence" (Fowler and Christakis 2010), representing total social distance from the original sender of information, with the greatest drop of influence occurring between the first and second degree of separation. Especially in a mass broadcast setting, in which content delivered is targeted to a large group of audience and thus less personal by design, the effectiveness of influence is likely to diminish over further distance from the sender (Papacharissi 2009). Thus, while social networks can reach many individuals quickly, influence and subsequent behavior change are likely determined by the network structure of WOM, in terms of distance from the sender and quality of content received.

### **2.2.2 Persuasive Communication and Charitable Giving**

The second stream of literature focuses on the processing of content received, addressing third research question. Prior research has identified communication process as exchanges of messages between a sender and a receiver, in which various aspect of each construct can affect how a recipient processes message content that can change her attitude and subsequent behavior (Eagly and Chaiken 1993; Kenrick et al. 2005; Perloff 2010). This theoretical framework is appropriate for the charitable giving context, in which an organization sends solicitation messages through mass media, mail, and most recently email, to ask people for a financial contribution or to volunteer. To overcome the difficulty of gaining compliance from recipients with such requests, senders employ various communication strategies. One type of compliance gaining strategies, known as self-referencing or personal relevance (Burnkrant and Unnava, 1989; Petty and Cacioppo 1980), attempts to raise recipients' issue involvement, so that they can relate the information to themselves and to their own experiences. For instance, acceptance to support requests by Susan G. Komen for the cure for breast cancer would likely be higher for women than men. A more subtle approach employs what is known as the "foot-in-the-door" technique, in which a sender asks individuals to perform a small favor that raises their issue involvement (Fraser 1966; Dillard 1990, Rittle 1981). This set of communication strategies is appropriate for *private* frame of decision setting, in which the recipients' level of issue involvement is high, prior to intervention by the message sender. However, when their motivation is low, these techniques are unlikely to achieve the target behavior (Meyers-Levy 1991).

By extending the decision frame from private to *interpersonal* setting, a sender can influence a recipient's compliance to message by transforming the decision outcome



from self-utility calculation to one in which the outcome depends upon both self-regarding and other-regarding preferences (Benabou and Tirole 2003). A second type of compliance strategies thus aims to build higher involvement with the sender by providing information about the sender such as credibility, likeability, and status (Bhattacharjee and Sanford 2006; Sussman and Siegal 2003). For instance, organizations frequently employ celebrities in their advocacy campaigns because recipients feel more connected and subsequently perceive conveyed information as more useful (Cacioppo et al. 1996; Haugtvedt et al. 1992; Kaufman et al. 1999; Priester and Petty 1995). Among many techniques of building source involvement is writing a simple “thank you” note to increase source likeability (Crusco and Wetzel, 1984; Lynn and Mynier, 1993; Leodoro and Lynn, 2007; Rind and Bordia, 1995, 1996).

When a persuasion attempt through source involvement is not feasible, information about involvement of other recipients may yield positive outcomes. For instance, when a message is echoed by a crowd of others, it builds credence to the argument quality and creates what is known as a “multiple source effect” (Harkins and Petty 1981). The effect of multiple sources on persuasion has been documented in social psychology and marketing fields (Harkins and Petty, 1981, 1983, 1987; Moore and Reardon 1987; Moore, Mowen, and Reardon 1994) by intensifying and eliciting more evaluative thoughts (Harkins and Petty 1987; Edell and Keller 1999). On the other hand, information about the presence of other receivers creates a different type of compliance by generating a perceived need to conform to social norm (Festinger 1954). Empirical studies from economics and social psychology have demonstrated that “social” information matters in predicting behavior across various contexts, especially in prosocial behavior or in the

“doing good” context (Andreoni 1989, 1990; Cialdini and Goldstein 2004; Frey and Meier 2004; Goldstein et al. 2008; Penner et al. 2005; Shang and Croson 2009; Weber et al. 2004). For instance, a study by Goldstein et al. (2008) shows social norms can induce residents to save more energy. A series of lab experiments drawing on behavioral economics literature have shown that information about others’ contributions positively influences a subject’s decision to give, which may arise out of conformity (Akerlof, 1982; Bernheim 1994; Jones, 1984) or the desire to enhance social image (Glazer and Konrad, 1996; Harbaugh, 1998). However, social information can negatively influence prosocial behaviors by increasing the likelihood of individuals “free riding” on others’ contributions (Benabou and Tirole 2003; Frey and Meier 2004), or when social information is presented with monetary incentives that can “crowd out” intrinsic motivation to “doing good” or enhancing image (Andreoni 1990; Ariely et al. 2009; Titmuss 1970). Taken together, the first stream of research predicts that information embedded in a message such as source, message, and others’ behavior is likely to affect prosocial behavior.

To summarize, past research has demonstrated the impact of social information on charitable giving behavior. A number of theories predict that an individuals’ contribution behavior is influenced by the behavior of others as well as the likelihood of information becoming diffused through social networks. This study uses data from a field study to evaluate the influence of social information on an individual’s donation behavior including the likelihood of making a donation and the amount of that donation.

## **2.3 Research Context**

I collected data from one of the first 501(c) nonprofit organizations (NPO) to conduct an online fundraising campaign on Twitter. The organization is one of the first to rely exclusively on Twitter to promote and solicit donations. Since 2010, the organization has conducted an annual week-long fundraising campaign. In its first year, the online campaign resulted in donations of approximately \$15,000 dollars. Contributions topped \$30,000 the following year.

The proceeds from the campaign help women entrepreneurs in developing nations to build schools for children. The campaign website provides information about the organization and beneficiaries and enables individuals to make direct charitable contributions online, via credit card or PayPal. A donor can dedicate the gift to her mother as a Mother's Day present, in which case a personal webpage is created, listing the mother's name, the donor's name, and the contribution amount, plus any personal messages from the donor. Because the organization is completely volunteer-run, the two co-founders primarily use Twitter to promote the campaign. Although most of the target participants are from the United States, the site is open to individuals from all over the world.

Before describing the data, I will describe briefly Twitter and how it facilitates interpersonal communication among users. Twitter.com is a platform that offers social networking through micro-blogging. By using an Internet-enabled device to send out tweets, short text messages of 140 characters or less, users can communicate with others on the site. A Twitter user can connect with other members by "following" or subscribing to their tweets. Subsequent tweets from the user will appear on the Twitter user's start

page or *tweets stream* in reverse chronological order. By default, a Twitter user's profile is public, meaning that her tweets are viewable to anyone.

A notable feature that shapes Twitter conversations is the asymmetric nature of communication. If User A subscribes to User B, all of User B's tweets appear in User A's tweet stream (or twitter feed). However, unless User B also subscribes to User A, the communication is one-sided. If User A and User B both subscribe to one another, then the nature of communication is referred to as bidirectional. To put it another way, messages transmitted by a sender can be read by all the other people connected to the sender's social network of friends. Celebrities who have many followers, most notably Lady Gaga or Justin Bieber, effectively use Twitter to maintain relationships with their followers (Lampe et al. 2006). For them, sending tweets is analogous to broadcasting advertisements via traditional mass media such as TV or radio without having to pay any substantial fee. In addition to the mass broadcasting feature, Twitter has a one-to-one or interpersonal communication function. Using a directed message prefaced by the "@" symbol and an individual's user name, a sender can communicate with one follower at a time, and this symbol may be a marker of a stronger tie between users (Papacharissi 2009). The public nature of Twitter enabling any user to follow anyone encourages interpersonal communication to increase rapidly.

While these features enable Twitter users to reach an extended audience, delivering tweets to followers does not necessarily guarantee that messages will be viewed by the receivers. An initial screen of a user's screen displays a feed or list of tweets in reverse chronological order, and as new messages are received, older messages will move towards bottom of the screen and eventually be removed from a user's view, thereby

reducing the likelihood of a message being read, unless a user decides to spend additional effort to scroll down to reveal previously hidden tweets. If a Twitter user is following many people, or if a sender's frequency of tweeting is high, information overload may occur when an individual is unable to view let alone process the messages (Jones et al. 2004). However, evidence for this argument is mixed, as Arguello et al. (2006) found no evidence that attention overload associated with high message volume led to messages being ignored. In other words, while all Twitter conversations are technically viewable in public, it is not practically or realistically public because browsing through large volume of tweets is inconvenient and takes time.

It is not surprising then given the short lifecycle of a feed and the potential information overload, user-created communication cues (McGrath 1984) such as acronyms, special symbols, emoticons, etc., are prevalent in Twitter conversations to capture a receiver's attention. For instance, most Twitter users are familiar with RT, an acronym for retweet, to indicate a message originated from another sender who is not directly connected to the receiver. As noted above, the "@" symbol indicates a shorthand for directed message.

This communication code may also serve a symbolic significance in terms of signaling the quality of the message. For instance, RT could signify filtered content, and the "@" symbol could indicate relevant content, thereby differentiating a particular message from the others that flow through a user's feed list. A message with a filtering symbol or a specific user being referenced is likely to be more useful to the intended user than to another user. In sum, followers will then draw conclusions on whether a message

is useful based on the indications of the intended recipients of the messages, the content of tweet messages, and the use of acronyms and special symbols (Papacharissi 2009).

## **2.4 Data Analyses**

I collected tweets that mentioned the fundraising campaign from the first week of May 2010 and 2011, which totaled approximately 10,090 messages sent by 2,960 individuals. I also obtained individual records of donations made to the organization through Paypal during the same periods. Based on name matching and interviews with the founders, I was able to identify and associate Twitter handles with Paypal receipts, resulting in approximately 265 unique donors with an average donation of \$45. From this data set, I converted sent messages data into the total number of messages received per user, based on follower relationship information. For donors, I removed the messages received after the time of donation according to Paypal records to estimate the effect of messages received on donation decision. Altogether, the number of tweets received for all participants was approximately 900,000, averaging 303 tweets received per user.

The nonprofit organization used Radian6, a well-known social media monitoring tool, to collect the tweets stream data sent during the online charitable giving analyzed in this study. I complemented this with Twitter API's to collect additional information on user profiles and follower relationships relevant for this study. In addition to this data, I obtained data from the organization who conducted a separate follow up survey of participants for robustness check. The survey identifies individual characteristics such as prosocial orientation, personality, and demographic information to control for biases and

strengthen the results. Together, the data used in this study capture a broader view of online communications and consumer behavior.

To answer the research questions stated above, I operationalized constructs into two categories of variables: (1) source characteristics and (2) message characteristics predicting donation behavior, in terms of probability of donation and contribution amount. In addition, I incorporate network characteristics as part of operationalizing both sets of variables. For instance, source characteristics depend upon to whom a receiver is connected, which reflects her social network. More specifically, I capture source characteristics in terms of the diversity of sources or the total unique number of senders (SRC\_DIVERSITY), the percentage of senders having a bi-directional follower relationship (BI\_TIE), and the average value of senders' influence (SRC\_INFLUENCE). These characteristics were measured using PageRank (Page et al. 1998), a well-known network metric to calculate the importance of a node in network (Newman 2003, 2004), and the nature of the relationship to the firm (MEMBER, NONMEMBER), where a member has a direct follower relationship to the firm, versus a nonmember who has two or more degrees of separation from the firm (e.g.: follower-of-follower, follower-of-follower-of-follower, etc.).

To operationalize and measure message characteristics, I used a text mining technique (Feldman and Sanger 2006) to extract and classify unstructured text data into categories of content. Text analytics techniques have become popular because of recent advances in computer science in automating the process of language processing based on linguistics theories (Pang and Lee 2008, Liu 2011). Recent studies applied text mining to analyze relationships between product attributes and sales (Archak et al. 2011), to estimate

demand for hotels (Ghose et al. 2012), and to predict the success of movie scripts (Eliashberg et al. 2007). More specifically, I use one technique called LDA (Latent Dirichlet Allocation ) based topic modeling (Blei 2012), which uses a probabilistic model based algorithm to assign a set of words contained in documents into topics or themes. The basis for a topic model rests upon the idea that a collection of words comprising a document are mixtures of topics, where a topic is a probabilistic distribution (e.g.: Dirichlet distribution) over words (Blei et al. 2003; Griffiths and Steyvers, 2002, 2003, 2004; Hofmann 1999, 2001). This procedure overcomes the difficulty of analyzing a large volume of unstructured data and reduces subjectivity inherent in content analysis.

The categories of content resulting from the topic modeling technique reflect various forms of persuasive content as part of compliance gaining strategies. As noted above, I present five categories of content drawing on persuasive communication literature. First, call-to-action (CTA) is an example of the foot-in-the-door (FITD) technique, requesting people to perform small favors. In this study, CTA represents a firm asking followers to tell others about the campaign and to visit the organization's website to learn more about the cause and beneficiary. Second, emotional appeal (EMOTION) is another persuasive attempt to raise a receiver's involvement by drawing attention to self-relevant information by making emotional connection such as one's mother. Third, offering a subsidy or matching donation from a sponsor (SPONSOR) reduces costs in making a donation. Fourth, offering "thank you" (THANKS) represents a persuasion technique to increase source likeability to enhance the interpersonal relationship between the sender and the receiver. Lastly, sharing others' act of donation (VISIBLE) invokes a perceived



need to conform to a social norm. I present a summary of topic words shown below **(Error! Reference source not found.)**.

Next, I further assign each content category based on the communication mode, whether a message was delivered through a mass broadcast or narrowcast (i.e. directed message). This is to test the effect of different whether certain type of content is better mediated in one form of communication modes in a donation decision. Not surprisingly, most messages were received via mass broadcast (~90 percent), and less than 10 percent of total tweets were received via narrowcast. Of these, I did not include about 27 percent of tweets of miscellaneous content categories that were not relevant for the study. I present a summary of the topic distribution shown below (Table 2.2). To capture the volume effect of broadcast types, I also calculated the relative occurrence of RT or retweet (RATIO\_RT), which is highly correlated to generic tweets, and directed tweets (RATIO\_@).

Third, the relative volume of content categories received may depend on the degrees of separation or how far a receiver is from the original source of communication. For instance, many conversations start from the nonprofit organization and diffuse through a series of connections. Therefore, degree of separation from the source is likely to interact with the content variables noted above. As noted above, the degree of influence drops off by two-thirds from the first to the second degree of separation (Christakis and Fowler 2010). I operationalized network distance as a dummy variable and define a member (MEMBER) as the receiver directly connected to the nonprofit organization, whereas a nonmember is likely to be removed from the nonprofit organization by at least two degrees or more. In a separate analysis, I calculated the average geodesic distance, a

widely used network metric to measure the shortest path between two agents. Each year of the fundraiser the short average geodesic distance of 2.49 and 2.46 ties, respectively, indicate that a single variable capturing network distance is justified. This implies that members receive both firm-generated and user-generated messages, whereas nonmembers receive firm generated message through members. Therefore, I further divided content categories into MEMBER and NONMEMBER only variables. The distribution of members in the sample is approximately 34 percent<sup>10</sup>.

For control variables, I adopted a user’s total follower count (FOLLOWERS), which is correlated with other user profile characteristics on Twitter, such as the number of users she is following as well as the total number of tweets. In addition, I captured various aspects of user activities during the campaigns such as when they started receiving tweets (START), the total number of tweets sent (TWTS\_SENT), and a year dummy. Lastly, I added control for individual characteristics by using recent developments from psychology and computational linguistics (Pennebaker and Francis 1996). This set of constructs known as psychometrics of natural language assigns value to measure three categories of personality dimensions such as (a) emotional (PERS\_EMOTIONAL), (b) social (PERS\_SOCIAL), and (c) analytical (PERS\_ANALYTIC) processes by analyzing their tweets. Lastly, Table 3 shows the summary statistics for the data, and Table 4 shows the pairwise correlations.

The main model I estimate is as follows:

$$\text{Donation (Probability, Amount)}_i = [\text{Source}]_i + [\text{Message/Member, Nonmember}]_i + [\text{Control}]_i + \varepsilon_i, (1)$$

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<sup>10</sup> For robustness check, the difference of amount donated between MEMBER (\$36.85) and NONMEMBER (\$48.08) is not statistically significant (F-value=0.52)

where [**Source**] = SRC\_DIVERSITY, SRC\_INFLUENCE, BI\_TIE, [**Message**] = CTA, EMOTION, SPONSOR, VISIBLE, THANKS, RATIO\_RT, RATIO\_@, and [**Control**] = FOLLOWERS, START, TWTS\_SENT, PERS\_EMOTIONAL, PERS\_SOCIAL, PERS\_ANALYTIC;

The dependent variables are the probability of donation and the dollar amount of donation. I estimate a Probit model for the first outcome and Tobit model for the second and run regressions with robust standard error. For each set of outcomes, I modify the main model by adding interaction terms between source diversity (SRC\_DIVERSITY) and content variables (CTA, EMOTION, SPONSOR, VISIBLE, and THANKS) to test for moderating effect. I show the results from regressions in Table 5. In models (1) and (2), I consider the nature of the broadcast (i.e. mass broadcast and narrowcast) on the content by member type and possible moderating role of source diversity in predicting donation probability. In model (3) and (4), I extend the model to predict the donation amount.

I first consider the implications of the results in Table 5. First, the regression results show in general that mass broadcast has negative influence, whereas narrowcast has positive influence on donation behavior, in terms of likelihood of donation and amount. In addition, donation behavior is strongly influenced by the strength of connections a receiver has with the sender. For instance, BI\_TIE has a positive and statistical significance. Second, this level of connection seems to determine which types of content are more effective. For members who are likely to have stronger ties with the sender, invoking social norms (VISIBLE) has a positive impact whereas offering a subsidy (SPONSOR) has a negative influence on donation behavior. For non-members, who are likely to have weaker ties with the sender, personal “thank you’s” (THANKS) are likely to be effective. However, asking for small favors (CTA) on behalf of the organization is

unlikely to generate target behavior for nonmembers. Lastly, multiple source effect (SRC\_DIVERSITY) has a positive impact on donation behavior in moderating content quality, specifically call-to-action (CTA). This full moderation effect (Finney et al. 1984; Jaccard et al. 1990; Bauer and Curran 2005) indicates positive association between call-to-action (CTA) content on donation outcome, conditional on above means diverse source. In other words, with “crowd” support, the perceived usefulness of performing small requests is likely to be enhanced, thereby increasing the likelihood of donation, especially for nonmembers.

Second, information about the nature of the broadcast has a different impact on members than nonmembers. In general, mass broadcast, which mediates generic content, in general has a negative influence on members, whereas personalized content through narrowcast mode has a positive impact for nonmembers. This is an important result and a contrast from previous work that has demonstrated that WOM can drive important outcomes (Chevalier and Mayzlin 2006). While WOM is effective in recruiting more people to spread information, a more meaningful outcome depends upon not only the type of relationships between the sender and the receiver but also the mediated content.

While the preliminary findings offer important insights for practitioners as well as academics, the data used in this study suffers from possible selection bias. That is, a donor may be different from a non-donor. While observable profile characteristics prior to campaign participation do not differ significantly between them, non-observable characteristics could add such bias to the model, thereby reducing the validity of the findings.

To address this issue, a follow up survey was designed with a 20-item survey questionnaire adopted from prosocial behaviors literature (Penner 2002) to measure individual characteristics that are commonly identified as influencing donation behavior such as altruism, empathy, other-orientation, and social responsibility. In addition, a 10-item Big-Five personality survey items were included to assess the dispositional characteristics of individuals that might affect their online activities. The survey was administered to randomly selected Twitter users with available emails. The online survey was administered with SurveyMonkey, and a total of 213 subjects responded, representing a 13 percent response rate. The survey items' reliability was assessed via Cronbach's alpha, and the minimum value was 0.76.

Again, the comparison of donors and non-donors using the survey results does not show any statistical difference, supporting that the result is robust against potential selection bias. The result of the selected items for comparison is shown below (Table 6).

## **2.5 Discussion**

I set out to explore how firms can increase customer engagement and revenue through social media. Using charitable giving as the research context, I demonstrate the value of information technologies in extracting, analyzing, and assessing the impact of social media on donation. A donation pattern within a network of users is shaped by a process of communication and social influence. The communication process, specifically embedded content, is presumed to shape the perceptions of people who seek to do social good or who are influenced by the masses, thereby motivating their donation decisions. Using the latest set of methodologies in business analytics, such as social network

analytics and text analytics, I derive insights that practitioners can quickly use to determine who the influential people are and how best to influence activities that will result in increased participation.

The contribution of this study is to both substantively and methodologically address the problem of accurately analyzing the information gathered on social media in order to understand what a firm should do to enhance the likelihood and amount of donation. First, it is important to note that persuasion occurs through establishing and cultivating interpersonal relationships. A simple act of following back a follower could return substantial dividends for organizations, increasing donation amount by 1.3% above mean charitable contribution. Second, recognizing what mode of communication is more relevant for immediate followers, and choosing what types of content to embed in a message is critical in engaging constituents. For instance, providing members with donation-specific information such as sharing others' donation behavior and donation matching can have both positive (\$14) and negative effect (-\$18), respectively. On the other hand, engaging non-members through personal communication is likely to yield more favorable result (~\$2) than broadcast communication. Third, multiple sources or crowds of participants can enhance message processing, especially for those who are further removed from the firm. For instance, asking non-members to participate by advocating small action is likely to result in negative impact on donation behavior; however, multiple senders repeating the same call to action is likely to yield positive behavior change.

Methodologically, this study is among the first to evaluate how online communications effect measurable business outcomes by leveraging new innovations in

business intelligence such as social network analytics and automated sentiment and topic modeling analytics. By studying linkage patterns among actors or other elements (Borgatti & Foster, 2003; Carley & Kaufer, 1993; Kadushin, 2004; Kilduff & Tsai, 2003), firms can identify the key players in a given domain, the relationships among them, and the patterns of change. Second, the unstructured and qualitative nature, as well as the ever increasing volume of social data, makes the task of extracting meaningful information challenging (Godes et al. 2005). By employing text mining and analysis techniques, practitioners can draw insights quickly and efficiently. Lastly, this study is among the first to show how information technology can create social value by promoting prosocial behavior (Batson 1998; Benabout and Tirole 2006), briefly defined as helping others. To date, this issue has been a vastly underemphasized area in the IS discipline.

To conclude, I have demonstrated how to combine social network analysis and text analysis to draw important insights. More specifically, social media monitoring services can quickly extract who is talking by how much. These people can become integrated to your existing constituents by following back and listen to their conversations. In addition, firms can selectively choose different levels of requests to increase participation. The question today is not whether firms should use social media, but how they should use the information their constituents are sharing on social media. Understanding what they are discussing can be used to attract more people to their mission and make fundraising campaigns more successful.

## **Chapter 3: Networks of Green People: Prosocial Behaviors in Online Communities**

### *Abstract*

Climate change poses significant challenges for society at large. Increasingly, policy makers are looking to address this important issue by mobilizing the masses through online communities. Using detailed data on member activities in a “green” online community, I demonstrate the value of information technology in creating an environment where others can observe and learn eco-friendly practices from other members. I show that a member’s total carbon savings is mainly influenced by her exposure to information about others’ green behaviors. More specifically, a member’s decision to perform a sustainable act is determined by the organizational structure and the strength of relationships she has with fellow members in her social network. While organizing members into groups decreases their effectiveness, especially in larger groups, a higher frequency of communication among members increases sustainable behavior by enhancing interpersonal connections. In addition, I show the moderating effect of groups on total carbon savings. This study is among the first to empirically examine the theoretical and practical implications of online networks on sustainable behaviors.



### 3.1 Introduction

Globalization is creating a consciousness of the world as a whole and interdependent of people and societies (Robertson 1992). Whether global communities can come together to solve a worldwide problem is another matter. Human-induced<sup>11</sup> climate change has escalated over the past 50 years and is “projected to continue and accelerate significantly if emissions of heat-trapping gases continue to increase”. The impact of climate change is imminent as evidenced by the recent Superstorm Sandy, which hit the northeastern part of the U.S. and caused billions of dollars in damage and other losses. Convincing ordinary citizens to practice “green” or sustainable behaviors<sup>12</sup> that compromise the needs of the present while preserving the environment for the future generation (Elliott 2011), however, remains a vital challenge for policy makers. Devising ways to ensure environmental sustainability requires large-scale human cooperation involving social, economic, and technological solutions (Kerr 2007; Dietz et al. 2003). More importantly, addressing this global dilemma requires overcoming selfish behavior while empowering *prosocial* behavior, defined as actions intended to benefit one or more people, often at a cost to oneself (Batson 1998).

Information systems scholars, in particular, have stressed the role of information technology as a method to influence individuals to practice “green” behaviors (Melville 2010; Watson et al. 2011). A study by Watson et al. 2010 suggests that information technology can play a vital role in building awareness and instilling green behavior in individuals. Studies suggest that social norms that value environmental sustainability

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<sup>11</sup> National Climate Assessment Development Advisory Committee (2013), Executive Summary, U. S. Global Change Research Program, accessed on January 12, 2013.

<http://ncadac.globalchange.gov/download/NCAJan11-2013-publicreviewdraft-chap1-execsum.pdf>

<sup>12</sup> From here onwards, I use “green” and sustainable behaviors, interchangeably.

might lead to more positive results (Goldstein et al. 2008) than economic and technological methods used to curb energy consumption through policies such as the “green tax”<sup>13</sup> and innovation such as energy monitoring devices, respectively. For instance, government-initiated recycling programs in the 1990s have employed techniques to activate social comparison by placing visible, colorful recycling bins in neighborhoods (Schultz 1999; Cialdini 2004), and several utilities have started to add information about the community’s average energy use for each customer in monthly utilities statements in recent years (Allcot 2010). Social norms serve as powerful guidelines for individuals in a group or community (Terry et. al. 1999), and members learn from others, whether the “other” is a familiar, next-door neighbor or an indiscriminate person in the neighborhood. This observational learning (Bandura 1997) is a well-established concept in social learning theory and has been found to influence individual behaviors in various contexts (Cai et al., 2009; Cheung et al., 2012; Liu, 2006).

However, the effectiveness of observational learning typically assumes physical proximity of the reference group as context through which members assess the importance of social norm. Examining social norm based on symbolic proximity on its influence in sustainability context has been an important gap in the literature. For instance, individuals who join “green” online communities can observe and learn from many others with whom they share common interest of saving the planet. However, they do not necessarily share the same physical boundaries, thus potentially reducing the effectiveness of social norm on individuals to save energy. I apply the theoretical framework to increase understanding of how information technology can foster

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<sup>13</sup> “Green taxes ‘would hit poor most’”. BBC News. October 26 2004.

sustainable behaviors in online communities by discussing and testing predictions of theory empirically.

This essay seeks to examine how different characteristics of social networks impact an individual's prosocial behavior, particularly in the context of environmental sustainability. Online communities are extended social networks of individuals and groups organized around shared interests or goals, and they can influence social norms on various issues (Butler 2001; Boyd and Ellison 2006). First, a member's choice of self-organizing such as a generic member having loose ties with all other members in the community, or a member belonging to a small, tight subgroup organized around a specific interest or shared affiliation within the community, affects the exposure of others' actions and the extent of their influence on prosocial behaviors (Charness et al. 2007, Chen and Li 2009, Chen and Chen 2011). For instance, the presence of a large group can decrease members' commitment level (Oliver and Marwell 1988). On the other hand, this can create more opportunity for interpersonal communication, which has been found to be positively associated with prosocial behavior (Isaac and Walker 1988; Kerr et al. 1997).

Second, the level of individual participation in online communities varies because a membership is largely voluntary (Moon and Sproull 2008), and many visitors to online communities do not stay (Arguello et al. 2006). However, some individuals do become permanent, highly active members, thus ensuring the survival of online communities (Bagozzi and Dholakia 2002, Lee and Cole 2003). This reality implies that the effect of observational learning in online communities is not necessarily consistent across all

members because each member's reason for joining an online community may differ (Brewer and Kramer 1986; Kramer et al. 1986; McClintock and Liebrand, 1988).

In summary, the nature of online communities supported by largely transient members with a few core members suggests that adoption and practice of sustainable behavior is dependent upon how organizational structures facilitate the members' social learning process. More formally:

- How does a member's choice of self-organizing (i.e. individual or team member) influence changes in individual's prosocial behavior over time?
- How do different network characteristics such as size and communication intensity influence changes in individual's prosocial behavior over time?

To answer these questions, I collected data from Carbonrally.com, one of the first online communities to promote "green" or sustainable practices by enabling people to show their personal accountability through measurable action. A member belonging to this online community can keep track of her list of activities called "challenges" and total carbon dioxide (CO<sub>2</sub>) savings attained by pledging and completing each "green" activity online. Each member can choose from a fixed number of challenges set by the community administrators with different levels of difficulty, as measured by the pounds of CO<sub>2</sub> reduced, such as taking public transportation to go to work or switching from plastic cups to coffee mugs. Once each activity is completed, the outcome is automatically posted on a member's personal webpage within Carbonrally.com that is visible for others to see. In addition, members may invite their friends or join other groups or "teams" of individuals. Last, a member can support other members' actions by

leaving comments on their web page, as well as team pages. All information such as profile pages, activities, and comments are public information.

There is extensive literature on what motivates individuals to behave prosocially, and a detailed review of this work is beyond the scope of this study. Briefly stated, a member decides to engage in sustainable behavior to satisfy at least one of three types of motivation: (a) self-efficacy or psychological reward derived from the act of learning what or how to practice sustainable behaviors (Giles and Eyster 1994, Yates and Youniss 1996), (b) psychological utility of “warm glow” in doing good deeds for others (Andreoni 1990), and (c) social identity maintenance (Gaertner et al. 2000) by complying with social norm (Butler 2011) or enhancing self-image in relation to others (Ariely et al. 2009). Collectively, these motivations require the presence of others to work, and a perceived social norm further determines a member’s course of action by either becoming highly active or “free-riding”<sup>14</sup> on other members’ efforts. For instance, a member guided by self-interest will decrease her efforts to be sustainable when she learns that her community’s social norm for it is weak. To put it another way, a member’s repeated actions constitute learning through observing and interacting with others and positive learning results in more energy conservation efforts, whereas negative learning leads to reduced efforts and possibly withdrawal from the community.

How a member learns about social norms and adjusts her behavior accordingly is likely to depend on the extent of her connection with others. Strong connections to another member or a reference group can enhance trust building and reduce the risk of free-riding behavior in others (Coleman 1988). On Carbonrally.com, three types of

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<sup>14</sup> Here, I use “free-riding” to describe the strategic behavior of an individual to accept the benefits of a collective action without making a positive contribution such as enjoying fresher air from a reduction in pollution.

connections exist. First, a member joining the website is automatically connected to a community of like-minded members dispersed across U.S., or even the world. However, this connection is relatively weak, and the tie that binds members together is shared interest and a goal to conserve energy. Second, a member who joins Carbonrally.com through affiliation with an organization is more likely to have stronger connections with fellow members. For instance, high school students join and organize themselves into teams, in which a team leader approves every membership, and they are more likely affected by the behaviors of fellow students than general members in Carbonrally.com. Thus, members in groups have indirect access to other members through a central figure. Last, a member who receives or extends a personal invitation can become a part of a network of interpersonal connections. Comparing the strength of the three types of ties may be difficult, but the extent of social influence exerted on members for each type can be characterized by the level of personal interest or conviction, group identity or attachment, and the strength of interpersonal bonds, respectively (Ren et al. 2012). These three types of connections on Carbonrally.com form two distinct organizational structures within the overall community: (1) team networks of affiliations or weak ties (Granovetter 1973) and (2) referral networks of personal connections or strong ties. A member can belong to one or both of these networks or none at all.

The presence of these online networks makes Carbonrally.com an ideal research setting to observe how an individual's connections to other members in a social network affects her prosocial outcomes in the sustainability context – specifically her willingness to reduce carbon emissions. While research has shown that social interactions in offline contexts have a significant impact on the environmental behaviors of individuals

(McKenzie-Mohr 2000), it remains to be seen to what extent online communities can realize the potential of fostering sustainable behaviors in practice.

My main hypothesis is that a member's choice of self-organizing (i.e. individual vs. team) affects the visibility of others' actions, and different types of network characteristics moderate the extent of observational learning she acquires and subsequent action. More specifically, I hypothesize that teams comprising of weak ties among members<sup>15</sup>, positively moderate prosocial behavior. Second, strong ties in the referral networks also positively influence prosocial behavior. Third, I hypothesize that network size, which can serve as important proxy for information about others, negatively influence prosocial behavior. Last, I hypothesize interpersonal communications that strengthen relationships among individuals, positively influence prosocial behavior. Based on 1,554 survey responses obtained from Carbonrally.com members, along with detailed records of their activities, the model I estimate identifies the effect of two learning types over time (i.e. positive change in learning vs. no change in learning), organizational structures (i.e. team vs. referral networks), communication, and interaction of these constructs on total carbon savings. I used controls for individual characteristics such as age, gender, personality, and environmental awareness as well as group identification measures to account for selection bias associated with team affiliation. To identify learning types over time, I track each member's historical records of completed challenges and assign a value based on the average difference of a member's effort in consecutive challenges. For instance, a positive value indicates prosocial learning, a negative value indicates selfish learning, and zero value indicates no learning.

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<sup>15</sup> Team structure comprising of weak ties connecting a pair of members through a team leader is equivalent to a 2-mode or affiliation network.

First, I compare the impact of individuals who do not alter their effort level against those who put extra effort over time upon observing others' behavior. Second, I show that organizing members into teams does not necessarily elicit higher efforts from members, especially when the number of team members increases, thereby reducing the effectiveness of per capita contribution to a team or community achievement (Kiyonari et al. 2000) as well as increasing selfish behaviors without control mechanism to punish such behaviors (Fowler 2005). In contrast, interpersonal connections have a positive influence on CO<sub>2</sub> savings. Third, I show the positive effect of communications on sustainable behavior, offsetting selfish behaviors. Methodologically, this study provides the first attempt to analyze individuals' sustainable behavior using field data from real online communities rather than the group or aggregate data analysis used in previous studies. In summary, I show that social networks can foster sustainable behaviors by amplifying social learning through observations and interactions with others.

The rest of the paper is organized as follows. Section 2 presents the theoretical motivation and review of relevant literature. Section 3 describes the research context. Section 4 presents the data analyses and results. The paper concludes with a discussion of the results and suggestions for future research in this area.

### **3.2 Literature Review**

I start by describing resource dilemmas brought about by humans and discuss relevant literature to set up a theoretical framework on how observational learning in online communities fosters sustainable behaviors. Drawing from these, I set up a research model



to analyze how online social networks help individuals to coordinate and organize collective efforts to reduce their carbon footprint.

### **3.2.1 Understanding Human Behaviors in Environmental Sustainability**

The advocacy of self-restraint in energy consumption is but one instance of social dilemmas (Brewer and Kramer 1986), situations in which individuals must decide whether to give up personal benefits for collective interest. A major challenge in designing policies to induce sustainable behavior is how to achieve positive and viable social outcomes while aligning incentives for individuals to reduce up their utility. According to rational choice theory and lab experiments (Hargreaves-Heap and Varoufakis 2004), the utility gained from sustainable practices dissipates quickly with repeated interactions (Isaac and Walker 1988; Ledyard 1995), predicting self-interested behavior will lead to the depletion of natural resources. While other lab experiments have shown that mechanisms to reduce self-interested behavior with altruistic punishment (Fowler 2005), in which a member chooses to punish another member's selfish behavior often at the risk of personal loss, or other forms of behavior monitoring (Fehr and Gächter 2000) can work, implementing such policies in practice requires coercive power to impose changes (Falkinger et al., 2000; Van Huyck et al., 1995), or the enforcement of an agreement (Andreoni and Varian, 1999), thus making such designs impractical. In addition, offering explicit incentives such as monetary savings can crowd out intrinsic motivation (Benabou and Tirole 2006; Fehr and Rockenbach 2003) such as altruism or image motivation (Ariely et al. 2009).

However, research has consistently shown that a considerable percentage of individuals choose to act in the collective interest (Sally 1995). One explanation of this outcome is that individuals respond to social norms of prosocial behavior (Cardenas 2004), and early research has shown that even a short period of interpersonal discussion can increase subsequent prosocial behavior in a social dilemma (Deutsch 1958, 1960; Loomis 1959). Several studies have replicated the positive effect of communication (Isaac and Walker 1988; Kerr et al. 1997; Ostrom and Walker 1989; Wilson and Sell 1997), concluding that opportunities to communicate with other participants in the dilemma increase prosocial behavior by enhancing group identity or generating a social norm (Kerr et al. 1997; Orbell et al. 1988). A key challenge in building shared conscience is the expectation that others will act in the collective interest (Kiyonari et al. 2000), and individuals will look for signals of assurance or trust (Hayashi et al. 1999; Kollock 1998). To mitigate this uncertainty, communication that conveys information about others' previous actions can have a positive effect by shifting the psychological frame of decision making from that of self-interest to an interpersonal one (Duffy and Feltovich 2002; Hamilton et al. 2003). Thus, the problem of social dilemmas, or more specifically, resource dilemmas, becomes one of providing information about the social norm of sustainable practices (Simpson 2004).

Fostering sustainable behavior, then, depends on how individuals learn about the perceived importance of environmental sustainability within a community (Greeno 2006). This view of learning within a social setting (Brown et al. 1989; Wenger 1998) posits that learning is situated in contexts and relationships, and changes in behavior stem from determining what is socially acceptable and what is not. For instance, some researchers

have found that collective guilt mediates decisions on whether to take action on important issues (Ferguson and Branscombe 2010). However, learning within communities or groups may not necessarily lead to changes in behavior (Friedlander 1983; Huber 1991), when an awareness of social norms does not overcome the desire to pursue self-interest. Individuals develop environmentally conscious behavior based on personal involvement, stemming from an attitude and knowledge of the ecological issues and solutions as well as empowerment that their contributions are meaningful and can have an impact (Hungerford 1996). Thus, for a wide range of individuals', readiness for action creates a dilemma as they evaluate what level of effort is necessary to be considered within the parameters of socially acceptable behavior.

When individuals have imperfect information and obtaining information is costly, they often imitate others' behaviors, hoping others know better (Banerjee 1992; Bikhchandani et al. 1992). This type of social influence is referred to as observational learning (Deutsch and Gerard 1955), and it has been widely used in research (Bandura 1997; Simpson et al. 2008). Several studies have shown that observational learning increases when people are able to observe the decisions of others prior to making their own decisions (Cai et al. 2009; Croson and Shang 2008; Duan et al. 2009). This learning process in which a person accepts information from others can be understood as informational influence, in which adopters infer their own utility by making a rational use of information generated by prior adopters (Young 2009), or normative influence, in which a person conforms to expectations of another person or group so as to match self-image with others (Deutsch and Gerard 1955; Park and Lessig 1977).

Observational learning, however, can serve different purposes in predicting the positive or negative impact of individual behavior. For instance, there are differences in individual preferences – some are intrinsically self-interest driven, whereas others have a higher regard for other people in their decision making process (Benabou and Tirole 2006; Kollock, 1998; McClintock and Van Avermaet, 1982). In addition, consideration for others may stem from a desire to enhance self-image or social status (Ariely et al. 2009). While these complex motives are difficult to tease out from observed behaviors, it is possible to classify behaviors into “prosocial” and “proself”, in which prosocials continue to exhibit prosocial behaviors, whereas proselfs decrease their prosocial behavior in response to a change in social setting or the passing of time (McClintock and Liebrand 1988; Messick and McClintock 1968; Van Lange 1999).

In summary, addressing environmental sustainability as a resource dilemma requires innovative solutions from economic, technological, and social perspectives. While observational learning to foster sustainable practices may be promising, providing information about others to participants efficiently may be difficult, and the desired effect on behavior change may not be uniform across individuals, thereby raising questions about implementing such program on a large scale (Stern and Gardner 1981). To counteract this problem, I look to the online communities as a platform to coordinate individuals and instill sustainable behaviors.

### **3.2.2 Fostering Green Behaviors through Online Communities**

With widespread adoption of the Internet, online communities of people with common or diverse interests (Preece 2000; Rheingold 1993; Sproull and Kiesler 1991) have emerged rapidly. By one estimate, 84% of Internet users have participated in an

online community (Horrigan 2001). Online communities serve as a platform for organizations to connect with customers for product innovation and customer support (Dellarocas 2006; El Sawy and Bowles 1997; Ogawa and Piller 2006), to provide consumers with useful information (Gu et al. 2007; Wasko and Faraj 2005) and emotional support (Maloney-Krichmar and Preece 2005), and to provide venues for ordinary citizens to discuss politics and social issues (Hill and Hughes 1998).

In online communities, prosocial behavior exists in a variety of contexts such as knowledge creation and exchanges, (Constant et al. 1996; Wasko and Faraj 2000), suggesting that social networks may be suitable to address climate change. Online social networks are increasingly important sources for new information (Granovetter 1973), and thus, individuals can increase their knowledge of environmental issues and of the specific actions they can take to reduce their carbon footprint. In addition, individuals can observe the behavior of others (Preece 2000), and the visibility of active contributors can enhance their reputation or status in online communities (Butler 2011). Therefore, the actions of image-motivated individuals can serve as models for those who are seeking information about socially acceptable behaviors to adopt.

First, online communities can enhance observational learning by organizing members into groups (Charness et al. 2007, Chen and Li 2009). Assigning members to an explicit group within the community increases group identity and attachment (Turner 1985; Turner et al. 1987), even when they did not know others in their group. Members who are attached to a group have higher commitment levels, evaluate their group members more favorably, participate more, and exhibit more helpful behaviors (Blanchard and Markus 2004; Hogg 1992; Meyer et al. 2002; Ren et al. 2007). However, increasing group size

can decrease the commitment and contribution level of members (Karau and Williams 1993; Oliver and Marwell 1988).

Second, online groups exert influence on members based on interest or interpersonal bonds (Ridings and Gefen 2004; Sassenberg 2002). Interest or topic-based groups are based on a purpose or specific interest where the commitment level varies based on the members' attachment to either the purpose of the group or the group as a whole. Bond-based groups are based on friendships with other members and the commitment is founded on an individual's personal connection with other members (Sassenberg 2002). Developing member attachment by strengthening group identity or interpersonal relationships, respectively, then can ensure higher participation and survival of online communities (Ren et al. 2012). For instance, interpersonal communication can build relationships in online communities by making group and individual activities repeatedly visible to each other (McKenna et al. 2002), and studies have shown that the action-based information provided in observational learning is effective in influencing consumer decisions (Liu, 2006; Cheung et al., 2012).

To summarize, past research has demonstrated the impact of social influence on sustainable practices and the potential of online communities as platforms to foster such behaviors on a large scale. A number of theories predict that an individuals' participation decision and her subsequent contribution level is influenced by the behavior of others as well as the connection she feels towards others. This connection to others is further determined by an individual's decision to join groups and further affected by size and communication she receives. This study uses data from a field study to evaluate the

influence of social information on an individual's sustainable behaviors in terms of learning defined as behavior change and total carbon savings.

### **3.3 Research Context**

I collected data from Carbonrally.com, one of the first online communities promoting “green” or sustainable practices. Since 2007, members have joined a community of environmentally conscious individuals to learn and contribute to efforts to save the environment by reducing their carbon footprint. When a member agrees to join Carbonrally.com, she can choose to participate as part of the whole community or to join a “team” or group, organized around a company, high school, university, or other themes such as movie lovers (i.e. Twilight) or “soccer moms”. As a member, she can pledge to do one or more “challenges” from a set of green activities or that she will complete within a specific time period. Each challenge has a webpage with a detailed description and potential CO<sub>2</sub> savings with the higher number indicating the amount of effort required. Once completed, accrued CO<sub>2</sub> savings and total counts of completed challenges will show up automatically on a personal webpage within Carbonrally, visible to everyone. This visibility of one's action serves as a public commitment (Halverson and Pallak 1978), raising issue involvement and increasing subsequent behaviors (Kiesler 1971; Pallak et al. 1980). Through completing challenges, members learn to increase self-efficacy (Giles and Eyler 1994, Yates and Youniss 1996). Last, members can share their activities through discussion, which results in building relationships.

Members can gauge social norms within a team or community. In teams, members observe summarized information about team activities in terms of total challenges, total

CO<sub>2</sub> saved, and the total number of members participating in collective efforts to save energy. How social norms affect a member's perception and behavior is likely to depend on an individual's motivation as well as her structural position in relation to others. For instance, not having enough exposure to other participants reduces an individual's payoff in the form of social recognition, whereas too many participants may decrease the relative value of her contribution.

### **3.4 Data Analyses**

I collected data consisting of individual activities reported for a “challenge” or task completed from November 2007 to January 2012. I reduced the data set to U.S. users, although the site is available worldwide. I excluded non-U.S. users because they consist of less than 5% of population, and many of the foreign registered accounts seem to be fake users, generated by web-spiders or bots. In addition, I only included members who have completed at least one of the following to remove non-active members: (a) completed at least one challenge, (b) recruited at least one member, or (c) posted at least one comment on either their team or member webpage within three months from the last day of sampling period. From this data selection, there are approximately 128,000 observations of challenge activities completed by 19,523 users.

From this set of users, I obtained data from the company who conducted a separate online survey to collect additional data about individual characteristics, such as prosocial orientation, personality, and demographic information, to control for biases and strengthen the results. The survey items for these constructs were adopted from various literatures. For environmental orientation construct, a 10-item scale was adopted from



New Environmental Paradigm (NEP) scale (Dunlap and Van Liere 1978). For prosocial orientation and personality constructs, a 20-item prosocial orientation (Penner 2002) and 10-item Big-Five personality scales, respectively, were adopted from psychology literature. Finally, standard demographic information items such as age and gender were included to capture control variables for the analysis. In addition, group identification items were included to address selection bias associated with team affiliation, to be discussed later. The online survey was administered with SurveyMonkey, with two follow up emails over a period of two weeks. A total of 1,554 subjects responded, representing an 8% response rate. The response rate is rather low, suggesting a possible non-response bias; however, a meta-study by Shih and Fan (2010) indicates that survey response rate of published studies in social science varies widely, as low as 7%. To detect a possible non-response bias, I compared a survey sample against the community population in terms of observed total carbon savings per member. Based on ANOVA test, the average CO<sub>2</sub> savings did not differ statistically (F-stat: 0.88). Table 1 shows a comparison of the survey sample and population. The survey items' reliability was assessed via Cronbach's alpha, and the minimum value was 0.76. Together, the data used in this study capture a broader view of online communities fostering sustainable behavior.

To answer the research questions for this study, I operationalize constructs into two categories of independent variables: (1) learning types of individuals and (2) organizational structures, influencing the outcome of sustainable behavior, measured in terms of total carbon savings. In addition, I incorporate individual characteristics and other control variables in the estimation model.

First, the level of effort that a member chooses to exert when first joining Carbonrally.com reflects her preference prior to observing and interacting with other members. Once a member observes and learns from others' behaviors, her subsequent level of effort may increase, decrease, or stay the same. To capture both dimensions of effort in terms of a member's willingness to contribute, as well as acquired learning, I operationalize individual learning into two variables. I operationalize a member's effort level in terms of the average CO<sub>2</sub> per challenge completed (EFFORT), and measure learning as taking the average value of the first-differenced CO<sub>2</sub> rating for successive challenges for the member's total completed challenges (LEARN). In other words, the difference of effort exerted in successive challenge constitutes learning acquired from undertaking an action, and the value is averaged over a member's entire activities to denote learning acquired over time. Using this measure, I capture both positive as well as negative learning acquired from both self and others.

Second, I operationalize organizational influence on individual behavior in terms of (a) the structural connection in terms of affiliation (TEAM) or acquaintance (PAGERANK), (b) size (SIZE\_TEAM), and (c) communication received (COMMENT\_TEAM, COMMENT\_USER). As mentioned above, a member's relationship develops by indirect and direct connections through teams (TEAM) and acquaintances (PAGERANK), respectively. The latter variable measures a member's connection with others in terms of referral or invitation; however, a dummy variable indicating referral has relatively high correlation with other variables, so I adopt a well-known network metric PageRank (Page et al. 1998) to calculate importance of a node in the referral network (Newman 2003, 2004). In addition to the structural connection with

others, the team size is also likely to influence a member's behavior (Butler 2001). I operationalize the size in terms of the total team members (SIZE\_TEAM) if a member belongs to a team. For instance, having more members could increase interactions, thereby increasing a member's motivation and performance. On the other hand, it could also increase free-riding behavior due to a lack of social monitoring or control. Last, I operationalize communication, which facilitates interactions among members, in terms of the comments received on a team page (COMMENT\_TEAM) if a member belongs to a team as well as comments received on a personal page (COMMENT\_USER).

For control variables, I operationalize individual characteristics in terms of environmental orientation, prosocial orientation, and demographic variables. I adopt New Environmental Paradigm scale (see Dunlap et al. 2000 for review), a widely used measure of environmental orientation published in 1978. Specifically, I use two dimensions: (a) anthropo-centric (ENV\_HUMAN), measuring the belief that nature exists primarily for human use, and (b) eco-crisis (ENV\_EXT), measuring the belief that environment is not facing immediate danger. For prosocial orientation, I adopt Prosocial Personality Battery (PSB; Penner, Fritzsche, Craiger, and Freifeld, 1995), which identifies empathy (EMPATHY) and helpfulness (ALTRUISM), to predict prosocial behavior. To capture individual differences, I adopt 10-item Personality Inventory (TIPI) to measure "Big-Five" personality dimensions (Gosling et al. 2003), and demographic variables such as age (AGE) and gender (GENDER). Of five dimensions, I use only agreeableness (PERS\_AGREE) and openness (PERS\_OPEN) because these two dimensions are associated with prosocial behavior (Gosling et al. 2003). Last, I calculate the duration of an individual's membership (DUR) as the number of days between the

last observed activities (i.e. challenge, referral, or comment) and the date joined. Table 2 shows the summary statistics for the data, and Table 3 shows the pairwise correlations.

The initial part of the analysis study explores how individuals' prosocial behaviors change over time in the marketplace by further refining the learning (LEARN) variable. According to literature on prosocial behavior, individuals with prosocial orientation may exhibit a greater level of prosocial behavior as well as act more selfishly upon learning more about the social norm. For instance, researchers in the field of experimental economics have shown through lab experiments on public provision of goods, in which subjects are asked to contribute to a public fund, that average subjects reduce their contribution amount upon repeated interactions, thereby increasing utility for self but reducing the social outcome (Isaac and Walker 1988, Andreoni 1988). This "free-riding" behavior has been replicated consistently. However, there are still substantive percentages of subjects who continue to make self-less contributions (Andreoni 1995), thereby raising questions about what motivates this type of behavior, but more important, clearly indicating that there are two types of individuals. The first type will continue to display prosocial behavior in spite of clear incentives against such behavior, whereas the second type learns to behave more selfishly with sufficient incentives. Similarly, the recognition of two types of individuals has been long noted in social psychology literature as "prosocial" and "proself" (De Cremer and Van Lange, 2001; McClintock and Liebrand, 1988; Smeesters et al., 2003), respectively.

I classify each member according to these two types, first type exerting more effort over time, whereas second type decreases effort over time, respectively. I also include a third type to indicate a group of individuals whose effort does not change over time. To

be more conservative of this classification of members based on the learning type, I use a cutoff point of +/- 1 lb of CO<sub>2</sub>, resulting in 33 percent and 10 percent of first and second type of learning, respectively (Figure 2).<sup>16</sup>

There is potential endogeneity in using the first-difference measure to identify learning behavior over time. However, while the learning variable might predict the amount of carbon saving for an ensuing period or two, it is unlikely that this measure is endogenous with total carbon savings a member achieves over her tenure in the community. To further explore this issue, I complement this measure with survey items to test whether the two identified member types are statistically distinct from one another, based on exogenous constructs such as personality, prosocial orientation, and group identity. Using two-sample t-test to compare means for the two types and baseline group with static learning, I find that the mean value of altruism construct for the first type of increasing effort over time (0.07,  $p < 0.05$ ) is statistically different than those of other two types ( $m = -0.15$  for decreasing effort group, and  $m = -0.01$  for baseline group  $p < 0.10$ ). In addition, the mean value of group identity construct for the first type ( $m = 0.25$ ) is also statistically different than those of and the second type ( $m = -0.17$ ,  $p < 0.01$ ) and baseline group ( $m = 0.14$ ,  $p < 0.01$ ). In other words, this necessitates estimating learning outcome as another dependent variable, or at least treat learning outcome as a mediating variable to predict total carbon savings.

I further compare how learning outcome against team assignment. Figure 3 shows the visualization of learning types against team affiliation. I plot quadratic fitted values of the average daily CO<sub>2</sub> saving per challenge against the duration of each member for each

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<sup>16</sup> Alternatively, the classification of members based on learning variable can be done using a cluster analysis. I have used a cluster analysis with kmeans of three clusters representing two identified types plus base group with static learning, yielding similar result.

learning type (i.e. prosocial, and “neutral” or no change as baseline). In comparing these two types of learning based on whether a member belongs to a team, baseline follows a pattern of decline over time. However, prosocial learning behavior increases significantly depending on the team affiliation, suggesting that group affiliation can render a positive impact on members whose effort increases over time.

Last, I include the interaction term between the learning type (LEARN\_PRO) with team related variables (TEAM, SIZE\_TEAM, COMMENT\_TEAM) in predicting total carbon savings. While this learning can be influenced by acquaintances (PAGERANK) as well, I do not include this interaction term since the website does not offer a feature that enables members to observe the behavior of acquaintances easily.

To simplify the model and subsequent discussion, I focus only on the first type (LEARN\_PRO) as mediating variable<sup>17</sup>, with the predicted value of learning type from the first stage equation using Logit model, to predict total carbon savings.

The two-stage model I estimate is as follows:

$$\begin{aligned} Learning_i = & [Organizational Structure]_i + [Size]_i + [Communication]_i \\ & + [Control]_i + \varepsilon_i, (1) \end{aligned}$$

$$\begin{aligned} \ln(CO_2)_i = & [Learning^*]_i + [Organizational Structure]_i + [Size]_i + [Communication]_i \\ & + [Control]_i + \varepsilon_i, (2) \end{aligned}$$

where [**Learning**] = EFFORT, LEARN, [**Organization Structure**] = TEAM, PAGERANK, [**Size**] = SIZE\_TEAM, [**Communication**] = COMMENT\_TEAM, COMMENT\_USER, and [**Control**] = ENV\_HUMAN, ENV\_EXT, ALTRUISM, EMPATHY, PERS\_EMOTIONAL, PERS\_AGREE, PERS\_OPEN, GENDER, AGE, DUR, DUR^2;\* indicates predicted value from first equation;

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<sup>17</sup> Alternative model specification could treat the learning type as a separate dependent variable.

The two dependent variables are learning type assignment, where a value of one indicates a member increases effort over time, and a total of CO<sub>2</sub> reduced (lbs) for each individual over time, respectively. The latter measure represents a member's total energy saving activities. The distribution of CO<sub>2</sub> reduced is positively skewed and log-transformed with zero inflation to approximate the normally distributed continuous variable. Given that the data is censored (Figure 1), I estimate a Tobit model to run regressions with robust standard error, with the lower bound at 0.41.

Finally, I address the potential selection bias associated with team selection by instrumenting the team variable with group identification constructs obtained from the survey and state residence association. First, group identification (Brown et al. 1986; Hogg and Hains 1996; Luhtanen and Crocker 1992) points out the importance of social groups to self in terms of current membership (GRP\_MEM), usefulness of the social group (GRP\_USE), and importance of the group to self (GRP\_IMP). These three items are used to predict a member's decision to join a team. Second, there are 50 states represented in the data set, so I use 49 dummy variables. Many members on Carbonrally.com join the site as a group. For instance, company teams like Seventeen or NBC use Carbonrally.com to promote in-company green behaviors. High school and college teams like Notre Dame have also joined the site together. People that join in groups are usually located in the same vicinity. These instrumental variables may predict team affiliation better. Similar arguments can be made for city location as instrumental variables for more granularity, but there are 4,904 cities represented in the sample, which can potentially reduce the number of observations required to run the estimation model.

The validity of these many weak instrumental variables can be tested using an F-statistic of greater than 15 in the first step of the two-step procedures (Woolridge 2010).

In summary, I modify the estimation model as follows:

$$\begin{aligned}
 \ln(CO_2)_i = & \text{EFFORT}_i + \text{LEARN\_PRO}_i + \text{TEAM}_i^* \\
 & + \text{PAGERANK}_i + \text{SIZE\_TEAM}_i \\
 & + \text{COMMENT\_TEAM}_i + \text{COMMENT\_USER}_i + \\
 & + \text{LEARN\_PRO}_i \times (\text{TEAM}, \text{SIZE\_TEAM}, \text{COMMENT\_TEAM})_i \\
 & + [\textit{Control}]_i + \varepsilon_i, \quad (2.1)
 \end{aligned}$$

where [**Control**] = ENV\_HUMAN, ENV\_EXT, ALTRUISM, EMPATHY, PERS\_EMOTIONAL, PERS\_AGREE, PERS\_OPEN, GENDER, AGE, DUR, DUR^2 (\*TEAM is instrumented with GRP\_MEM, GRP\_USE, GRP\_IMP, and ST\_ID);

Table 4 shows the result of the two-stage regressions, with the Logit model for the first stage (column 1) and the Tobit model with instrumental variable for the second stage (columns 2 and 3). First, I compare the effect of joining a group of members (TEAM) against referrals (PAGERANK) on both the learning outcome as well as total carbon savings. I further compare the effect of size (SIZE\_TEAM) as a proxy for information members acquire about team performance such as team carbon savings.<sup>18</sup> In addition, I compare the effect of different communication patterns on carbon reducing activities. The communication patterns strengthen relationships among members. The types of communication exchanged include a posting on a team page (COMMENT\_TEAM) and a direct posting on a user page (COMMENT\_USER). I also consider the moderating effect of team related variables on the learning process. I control for individual characteristics

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<sup>18</sup> Correlation between team size and team total carbon savings is 0.8463



such as environmental orientation, prosocial orientation, personality, gender, age, and member's tenure (DUR).

First, the regression results in Table 4 show that carbon savings behavior, in terms of total pounds of carbon dioxide reduced, is strongly influenced by the effort and learning a member has acquired. Not surprisingly, the more effort one exerts in completing a challenge, the more likely it is that the total output of carbon savings will increase, as indicated by the positive and statistically significant coefficient on the variable EFFORT<sup>19</sup>, approximately 4.4% increase in total carbon savings. Likewise, members who increase effort over time (LEARN\_PRO) is likely to increase total carbon savings by 2.3%.

More important, the strength of connections a receiver has with other members through team affiliation and personal acquaintance is statistically significant. However, while indirect connection through teams (TEAM) is positively associated with the learning outcome, increasing the likelihood of behavior change by 36%, it is negatively associated with total carbon savings, decreasing by 85% compared to non-team members. On the other hand, direct connection with acquaintances (PAGERANK) is positively associated with the both learning as well as total carbon savings, suggesting that stronger connections with other members are likely to increase a member's sustainable behavior. In addition, increasing member size in terms of team members (SIZE\_TEAM) further exacerbates this behavior, indicated by negative coefficients on both variables, respectively. However, this size effect, which is a proxy for what members learn about

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<sup>19</sup> The initial effort may be comparatively high to effort exerted in the later stage of a member's tenure, thereby raising potential issue with the validity of the measurement; however, the initial effort measure over first ten and forty periods, respectively, has high correlation (0.9257) with the overall effort measure.

team effort, is counterbalanced through interpersonal communications (COMMENT\_TEAM).

Third, the interaction term between team affiliation and learning type on total carbon savings shows that increase effort change over time is fully moderated by team affiliation (Finney et al. 1984; Jaccard et al. 1990; Bauer and Curran 2005). In other words, team promotes positive learning on members to exert more efforts over time. Together, these results support a notion that online networks facilitate positive learning process for team members.

### **3.5 Discussion**

I set out to explore how online communities can foster groups of individuals to organize and empower each other to address a resource dilemma brought by a climate change. Using “green” online communities as research context, I demonstrate the value of information technologies in facilitating sustainable behaviors by making personal action visible to an online community. Organizing and communicating with other members shapes the process of social influence in a network of users. While online communities provide a platform where a crowd of people can gather quickly and easily for a particular purpose, a collective of loosely connected members does not necessarily imply shared conscience. While a subset of members who are intrinsically motivated may continue to perform strongly, the rest of the crowd in the community may leverage observational learning to act more selfishly.

I demonstrate, however, the positive effect of online communities on sustainable practices through direct connections and interpersonal communication among members.

One explanation of why this occurs is because simply knowing what others do through observing either individual or aggregate acts does not necessarily create bonds between members. Rather, only through building closer connections with others who are working towards a collective goal results in a higher level of motivation. In other words, networks can positively moderate observational learning, conditional on increasing relational strength between members through personal connections and frequent interactions. Conversely, individuals motivated by peer connections and interpersonal communication may leverage online communities as part of a self-promotion strategy. This line of reasoning is consistent with the image motivation hypothesis (Ariely et al. 2009) – that image conscious individuals will behave more prosocially given sufficient incentives exist to enhance their social standing.

The contribution of this study provides a substantive and methodological solution to the global dilemma of how to support grassroots movements through online communities. First, it is important to note that online networks create opportunities for many interested individuals to interact with like-minded individuals. A simple act of joining groups or teams can spur activities and produce a substantial reduction in an individuals' carbon footprint. Second, to maintain engagement and motivation with the site and its purpose, it is critical to create certain organizational aspects and to enable features that facilitate interpersonal communication. Lastly, this study is among the first to show how information technology can create social value by promoting prosocial behavior (Batson 1998; Benabou and Tirole 2006), briefly defined as helping others. To date, this topic has been a vastly underemphasized area in the IS discipline.

Methodologically, this study is among the first to evaluate how online communities facilitate observation learning to foster sustainable practices. By tracking members' behavioral patterns, group and organization leaders can identify proper incentives and interventions to encourage prosocial behavior while reducing free-riding behavior. For instance, a group leader can identify prosocial types can communicate to other members in a team in a way to enhance her social image. To conclude, online communities can promote environmentally conscious behavior by mobilizing individuals to collective action by increasing personal connection and building relationships through communication.

## Chapter 4: Conclusion

Since the introduction of the Internet at the turn of the last century, our society has gone through changes in a way that no one could have imagined. Helping others to create a better society is greatly facilitated by information technologies and social media. Information cascading through social networks helps individuals to make a more informed decision. However, more and better information does not necessarily imply a positive outcome for society, as individuals whose goals may not align with those of society. Rather, information that serves to increase interpersonal engagement is more beneficial, and my dissertation will make a significant contribution to understanding the impact of prosocial behaviors on society, in terms of both theory and practice.

The first essay is among the first to systematically examine an emerging business model for nonprofit organizations and social entrepreneurs. It will make a significant contribution to the literature on charitable giving behavior as well as to our understanding of how online social media impact individuals' prosocial behaviors. Whereas many studies have examined prosocial behaviors and information diffusion separately, this study is among the first to empirically examine how different communication patterns affect the flow of information and subsequently individuals' decision to donate.

The findings from the first study suggest that social media is effective in online fundraising. A few dedicated individuals can quickly increase the number of participants by sending tweets and encouraging others to spread the message using *retweets*. More importantly, volunteers can incorporate informative messages and cultivate stronger relationships with other members to increase donation efforts. A disclosure of donation information about others, however, may negatively impact one's motivation to donate.

Accordingly, fundraisers need to consider their communication strategies in their fundraising and relationship cultivation efforts.

The second essay is among the first to systematically examine the design of online communities to support grassroots efforts towards environmental sustainability. Unlike traditional grassroots efforts to save the environment, such as programs to increase recycling in neighborhoods (Cialdini et al. 1990), this study is among the first to empirically show that online communities induce sustainable behaviors by extending offline social networks to online platforms and by enabling community engagement through increased communications.

The findings suggest that greater social value can be created through rapid growth of participants, coordination of individuals and actions, and incentivizing prosocial behavior. However, the findings also suggest that growing too quickly has an adverse effect on a group, as members need sufficient time to cultivate relationships with each other. Further, while the ease of access in inviting multiple friends to join a group may increase the total social impact, this growth may inadvertently reduce interaction and subsequently discourage participation. In summary, these findings suggest that a successful community could increase communication among members to counterbalance the problems associated with quick growth.

Together, the implications of these two studies on the impact of social network characteristics and communication strategies on prosocial behaviors may also be useful for policy makers in nonprofit and governmental organizations as well as social entrepreneurs interested in rallying the masses for collective action such as voting, volunteering, and charitable contribution.

## Appendices for Essay 1

Table 2.1 Topic Words

<b>Topic</b>	<b>Words</b>
Call To Action (CTA)	url help now school tanzania build kids doing tweet join one create tag note
EMOTION	mother happy special idea gifts never mom url all best moms ever time change
SPONSOR	gift u honor dollar win too follow card dollar k get match women raised invest
THANKS	much thanks great show url amazing support sharing how re hope thank did very
VISIBLE	url love heartspace world enough see post live here

Table 2.2 Topic of Distribution (% of Total)

<b>Topic</b>	<b>Narrowcast</b>	<b>Mass Broadcast</b>
CTA	2.21	23.07
EMOTION	1.60	15.34
SPONSOR	2.33	12.03
THANKS	0.55	6.73
VISIBLE	0.72	8.35

Table 2.3 Summary Statistics

<b>Variable</b>	<b>Description</b>	<b>N</b>	<b>Mean</b>	<b>SD</b>	<b>Min</b>	<b>Max</b>
AMT	Donation Amount (\$)	2793	2.91	15.20	0	275
Donated	Whether donated	2793	0.09	0.28	0	1
BI_TIE	Percent of bi-directional ties	2793	50.28	48.81	0	100
SRC_DIVERSITY	Total number of unique sources	2793	18.31	26.47	1	224
SRC_INFLUENCE	Average PageRank score	2793	5.05	3.52	0.23	23.95
CTA	Message content - call to action	2793	23.88	10.34	0	100
EMOTION	Message content - emotional appeal	2793	15.88	8.39	0	75
SPONSOR	Message content - sponsor/matching	2793	12.47	6.72	0	88.9
THANKS	Message content - thanks	2793	6.94	8.32	0	100
VISIBLE	Message content - visibility of others' donation	2793	8.65	4.22	0	45
RATIO_RT	Ratio of Retweets to Tweets	2793	0.34	0.27	0	2.20
RATIO_@	Ratio of Directed message to Tweets	2793	0.02	0.11	0	3.00
U_FERS	Total number of followers	2793	7488.59	29864.08	0	398070
START	First day tweets received	2793	2.46	1.79	1	12
TWTS_SENT	Total number of tweets sent	2793	0.31	1.17	0	38.125
MEMBER	Firm follower	2793	0.34	0.47	0	1
PERS_EMOTIONAL	Personality - Emotional	2059	37.54	17.46	0	100
PERS_SOCIAL	Personality - Social	2059	49.28	21.54	4	100
PERS_ANALYTIC	Personality - Analytical	2059	46.78	20.52	9	100



Table 2.4 Pairwise Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	
(1) AMT	1																		
(2) Donated	0.63	1																	
(3) BIE_TIE	0.13	0.21	1																
(4) SRC_DIVERSIT	0.15	0.20	0.03	1															
(5) SRC_INFLUENC	0.01	-0.02	-0.13	-0.10	1														
(6) CTA	0.00	0.02	0.11	-0.01	-0.11	1													
(7) EMOTION	-0.01	0.01	0.07	0.01	-0.14	0.26	1												
(8) SPONSOR	0.01	0.04	0.08	0.02	-0.12	0.15	0.20	1											
(9) THANKS	0.01	0.02	0.17	0.06	-0.18	0.15	0.22	0.07	1										
(10) VISIBLE	-0.03	-0.05	0.11	-0.01	-0.28	-0.05	0.24	-0.08	0.13	1									
(11) RATIO_RT	0.00	-0.02	0.08	0.01	-0.07	0.17	0.19	0.13	0.23	-0.01	1								
(12) RATIO_@	-0.02	-0.03	-0.07	-0.08	0.03	-0.06	-0.06	-0.06	-0.06	-0.09	0.19	1							
(13) U_FERS	0.01	-0.01	-0.12	0.32	-0.01	-0.01	0.00	0.00	0.00	-0.04	0.02	0.05	1						
(14) START	-0.09	-0.11	-0.20	-0.36	0.11	-0.02	-0.09	0.04	-0.28	-0.32	-0.16	0.11	-0.05	1					
(15) TWTS_SENT	0.17	0.27	0.19	0.14	-0.02	0.04	0.00	0.03	0.02	-0.03	-0.01	0.01	-0.03	-0.06	1				
(16) PERS_EMOTIO	-0.07	-0.09	-0.05	-0.14	0.01	0.03	0.05	0.01	-0.01	0.01	-0.02	0.02	-0.04	0.09	-0.09	1			
(17) PERS_SOCIAL	0.03	0.08	-0.03	0.12	-0.01	0.01	0.00	-0.02	-0.01	-0.05	0.04	0.01	0.06	-0.08	0.08	-0.10	1		
(18) PERS_ANALYT	-0.04	0.00	-0.06	0.08	0.02	0.01	0.00	-0.01	0.00	-0.05	0.04	0.02	0.08	-0.03	-0.02	0.14	0.29	1	

Table 2.5 Regression Results

DV: Donated, Amount (\$)	(1) Probit		(2) Probit		(3) Tobit		(4) Tobit	
Variables	Coef	z	Coef	z	Coef	t	Coef	t
<i>Source Characteristics</i>								
BI_TIE	<b>0.0083</b>	5.78	<b>0.0084</b>	6.22	<b>0.5912</b>	6.75	<b>0.5841</b>	6.71
SRC_DIVERSITY	<b>0.0066</b>	3.32	-0.0159	-1.18	<b>0.3987</b>	3.23	-0.8151	-1.05
SRC_INFLUENCE	-0.0145	-0.79	-0.0147	-0.69	-0.8110	-0.65	-0.8988	-0.73
<i>Message Characteristics</i>								
[Message X Member]								
(Member)								
CTA_MASS	0.0038	0.12	0.0104	0.26	1.3994	0.64	0.4080	0.17
EMOTION_MASS	0.0670	1.29	0.0308	0.48	3.8852	1.11	2.7996	0.74
SPONSOR_MASS	<b>-0.2929</b>	-3.85	<b>-0.3034</b>	-3.32	<b>-18.0889</b>	-3.38	<b>-18.1926</b>	-3.21
VISIBLE_MASS	<b>0.2012</b>	1.81	<b>0.2749</b>	2.12	8.2378	1.12	<b>14.2330</b>	1.79
THANKS_MASS	0.0495	0.83	0.0493	0.66	3.6822	0.86	3.2181	0.70
THANKS_NARROW	-0.0332	-2.00	-0.0370	-0.40	-1.9701	-0.41	-2.0701	-0.43
RATIO_RT	1.1793	1.61	0.6589	1.25	119.2721	1.23	109.4971	1.01
RATIO_@	14.3452	1.29	15.6508	1.23	933.8359	1.58	912.5880	1.55
(Nonmember)								
CTA_MASS	<b>-0.0172</b>	-2.32	<b>-0.0285</b>	-2.45	<b>-1.1421</b>	-1.71	<b>-1.9655</b>	-2.62
EMOTION_MASS	-0.0028	-0.34	-0.0089	-0.97	0.0118	0.02	-0.2637	-0.45
SPONSOR_MASS	0.0032	0.32	0.0048	0.35	0.2852	0.37	0.4002	0.47
VISIBLE_MASS	0.0123	0.87	0.0178	0.98	0.7626	0.70	1.2589	1.10
THANKS_MASS	0.0024	0.45	-0.0024	-0.25	0.2175	0.44	0.1313	0.24
THANKS_NARROW	<b>0.0312</b>	3.56	<b>0.0288</b>	3.36	<b>1.9796</b>	3.85	<b>1.8619</b>	3.70
RATIO_RT	<b>-0.8996</b>	-3.14	<b>-0.6499</b>	-2.46	<b>-54.8329</b>	-2.40	<b>-57.9442</b>	-2.44
RATIO_@	-0.0298	-0.06	-0.1941	-0.42	9.9071	0.24	7.1766	0.17
[Message X Source Diversity]								
SRC_DIV*CTA			<b>0.0012</b>	2.24			<b>0.0871</b>	2.77
SRC_DIV*EMOTION			0.0011	0.96			0.0566	0.80
SRC_DIV*SPONSOR			-0.0007	-0.56			-0.0214	-0.29
SRC_DIV*VISIBLE			-0.0021	-1.11			-0.1653	-1.44
SRC_DIV*THANKS			0.0009	0.76			0.0091	0.12
MEMBER	0.3285	1.14	2.3609	0.97	0.3378	1.38	1.6789	1.61
<i>Recipient Characteristics</i>								
FOLLOWERS	0.0000	-1.21	0.0000	-1.29	-0.0001	-0.89	-0.0001	-0.79
START	-0.0864	-1.54	-0.0828	-1.45	-5.1548	-1.47	-5.8130	-1.61
TWTS_SENT	<b>0.3570</b>	2.47	<b>0.3542</b>	6.59	<b>4.9832</b>	2.48	<b>4.9117</b>	2.45
[Personality]								
PERS_EMOTIONAL	-0.0035	-1.15	-0.0026	-0.90	-0.1815	-1.03	-0.1435	-0.81
PERS_SOCIAL	0.0061	1.28	0.0068	1.16	0.4685	1.45	0.4963	1.60
PERS_ANALYTIC	-0.0025	-0.81	-0.0031	-0.93	-0.2917	-1.46	-0.3123	-1.57

Year Dummy: 2011	<b>-0.4611</b>	-2.61	<b>-0.4401</b>	-2.13	<b>-20.1404</b>	-1.64	<b>-22.8825</b>	-1.77
_Cons	<b>-1.5052</b>	-3.49	<b>-1.2967</b>	-2.25	<b>-108.1711</b>	-2.92	<b>-89.0233</b>	-2.40
N	2059		2059		2059		2059	
Chi-sq	291.32***		438.74***		348.18***		356.66***	
Pseudo-R2	0.3149		0.3214		0.1048		0.1074	

Note: z-statistics and t-statistics are presented next to the coefficient estimates. For all coefficients with p-values below 0.10, the coefficient estimate is presented in bold.

Table 2.6 Survey comparisons of Donors and Non-Donors

Characteristics	Non-Donors	Donors
Altruism	6.11	6.11
Empathic Concern	6.04	6.11
Personality - Agreeableness	5.24	5.51

## Appendices for Essay 2

Figure 3.1 Distribution of total carbon savings (log-transformed)

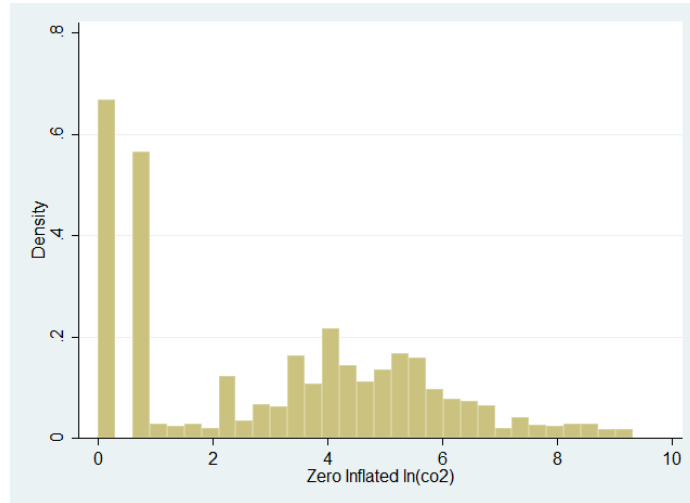


Figure 3.2 Distribution of Learning Types

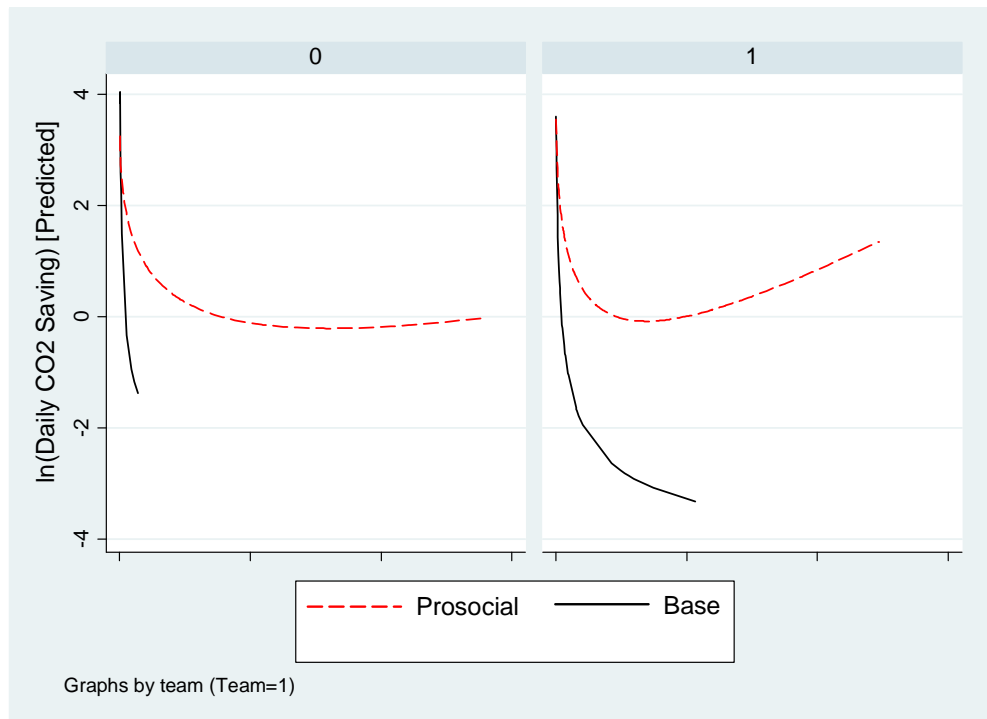
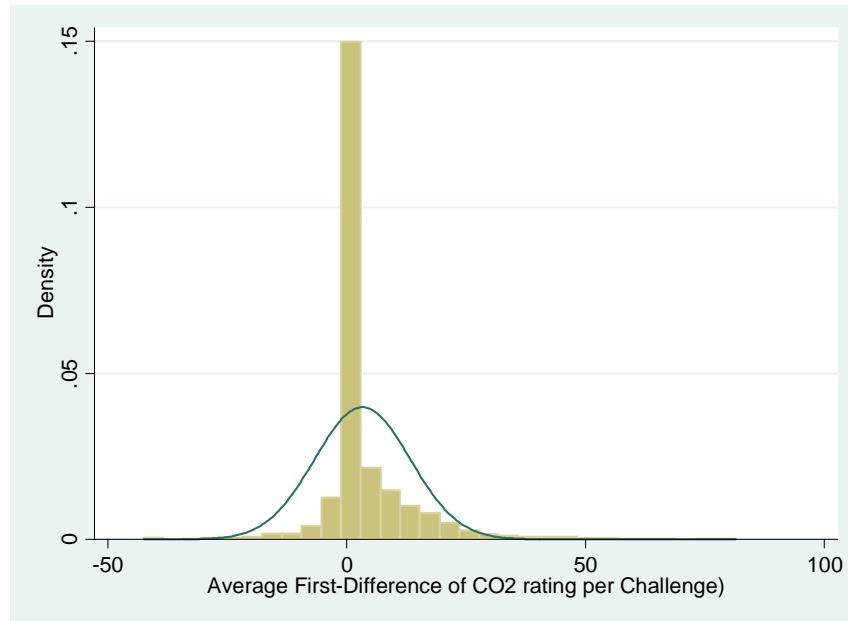


Figure 3.3 ln(Daily CO2) Savings by Learning Types and Team Affiliation

Table 3.1 Survey Sample

	<b>N</b>	<b>Team %</b>	<b>Avg. CO<sub>2</sub> Saved</b>
Population	19523	71.53	865.54
Survey Sample	1554	74.52	959.74

Table 3.2 Summary Statistics

Variable	Description	N	Mean	Std. Dev.	Min	Max
ln(CO2)	Total CO2 Saved (log-transformed)	1554	3.0990	2.5257	0	9.33
LEARN	Average first-difference of CO2 per challenge	1554	2.6479	9.1573	-42.5	81.5
EFFORT	Avg. CO2 per Challenge	1554	20.8551	26.8134	0	200
TEAM (1=Team Member)	Whether a member belongs to a team	1554	0.7452	0.4380	0	1
PAGERANK	Member importance in network	1554	0.1934	0.6761	0	20.20
SIZE_TEAM	Number of members in a team (divided by 100)	1554	15.6953	28.8239	0	95.1
COMMENT_TEAM	Avg. comment received per member in a team	1554	0.2117	1.9555	0	40.44
COMMENT_USER	Avg. comment received from another user	1554	0.0069	0.0796	0	1.17
DURATION	Length of stay (days) in community	1554	303.8972	423.6570	1	1489
ENV_HUMAN	Environmental Orientation - Humans responsible	1084	-0.0026	1.0028	-4.78	1.88
ENV_EXT	Environmental Orientation - Climate change crisis	1084	-0.0006	1.0018	-3.66	4.46
ALTRUISM	Altruism	1084	0.0159	0.9977	-3.88	4.86
EMPATHY	Empathy	1084	0.0060	1.0015	-3.86	4.57
PERS_AGREE	Personality: Agreeableness	1406	5.2060	1.0572	2	7
PERS_OPEN	Personality: Openness	1406	5.4752	0.9786	2.5	7
GENDER (1=Female)	Gender	1009	0.7549	0.4304	0	1

Table 3.3 Pairwise Correlations

(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
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(1) ln(CO2)	1														
(2) LEARN	0.40	1													
(3) EFFORT	0.65	0.21	1												
(4) TEAM	-0.12	0.00	-0.15	1											
(5) PAGERANK	0.18	0.08	0.08	0.06	1										
(6) SIZE_TEAM	-0.11	-0.08	-0.07	0.31	0.10	1									
(7) COMMENT_TEAM	0.12	0.09	0.03	0.07	0.03	-0.05	1								
(8) COMMENT_USER	0.03	0.00	0.03	0.00	0.00	-0.05	0.04	1							
(9) DURATION	-0.15	0.10	-0.20	-0.07	0.08	0.08	0.00	-0.06	1						
(10) ENV_HUMAN	0.15	0.03	0.10	-0.17	0.02	-0.08	-0.02	0.05	0.02	1					
(11) ENV_EXT	-0.02	0.02	-0.01	0.03	0.03	0.08	0.04	0.03	0.05	0.00	1				
(12) ALTRUISM	0.06	0.08	0.06	0.00	0.06	-0.04	0.05	-0.05	0.01	0.04	0.15	1			
(13) EMPATHY	0.01	0.01	-0.01	0.01	0.02	0.06	-0.02	0.06	0.02	-0.02	0.18	0.00	1		
(14) PERS_AGREE	0.03	0.04	0.00	0.01	-0.01	0.02	-0.02	0.01	0.01	0.05	-0.08	-0.07	-0.01	1	
(15) PERS_OPEN	0.07	0.00	0.06	-0.04	0.07	0.03	0.04	0.05	-0.01	0.16	-0.05	0.01	-0.05	0.19	1

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Table 3.4 Regression

DV: Prob (Learn=1), ln(CO2)	First-stage (1=Effort Change)		Second-stage (Total CO2 Savings)			
	<b>Logit</b>		<b>Tobit (IV)</b>			
	Coef.	z	Coef.	z	Coef.	z
<i>Learning</i>						
EFFORT	<b>0.0271</b>	7.40	<b>0.0440</b>	7.50	<b>0.0437</b>	7.49
LEARN_PRO			<b>0.0236</b>	2.39	-0.0069	-0.6
LEARN_PRO X TEAM					<b>0.0486</b>	5.62
<i>Structural Connection</i>						
TEAM	<b>0.3633</b>	1.81	<b>-0.8575</b>	-3.10	<b>-1.2762</b>	-4.23
PAGERANK	<b>0.9511</b>	4.52	<b>0.4447</b>	2.56	<b>0.2986</b>	1.72
<i>Size</i>						
SIZE_TEAM	<b>-0.0145</b>	-4.13	<b>-0.0174</b>	-1.84	<b>-0.0412</b>	-4.21
<i>Communication</i>						
COMMENT_TEAM	<b>0.3459</b>	2.35	<b>0.0914</b>	2.60	<b>0.0756</b>	2.16
COMMENT_USER	-5.1601	-0.76	0.4046	0.47	-0.0672	-0.08
<i>Control</i>						
ENV_HUMAN	0.0753	0.93	0.0834	1.23	0.1977	0.83
ENV_EXT	-0.1311	-1.59	0.0131	0.19	0.0299	0.43
ALTRUISM	0.0598	0.74	0.0872	1.31	0.0129	0.19
EMPATHY	0.0510	0.63	0.0085	0.13	0.0158	0.24
PERS_AGREE	0.1760	1.26	0.0165	0.25	-0.0127	-0.19
PERS_OPEN	-0.0709	-0.87	-0.0737	-1.12	-0.0273	-0.41
GENDER	0.1666	0.86	0.1145	0.71	0.1054	0.66
AGE						
20's	-0.4607	-1.51	-0.0382	-0.14	0.0465	0.18
30's	<b>-0.7081</b>	-1.90	0.3576	1.07	0.4925	1.48
40's	-0.5793	-1.53	0.1392	0.44	<b>0.5355</b>	1.67
50's	<b>-0.7079</b>	-1.94	0.3662	1.13	0.5142	1.59
60+	-0.7629	-1.81	0.2307	0.61	0.4501	1.2
DUR	<b>0.0011</b>	5.38	0.0017	0.92	0.0019	1.02
DUR^2			<b>0.0000</b>	-1.77	<b>0.0000</b>	-1.96
_cons	<b>-2.4760</b>	-3.82	<b>2.3402</b>	4.25	<b>2.8584</b>	5.08
N	1009		1009		1009	
Chi-sq	176.39		1075.89		1106.24	
Wald test of exogeneity			29.42		32.85	

Note: z-statistics are presented next to the coefficient estimates. For all coefficients with p-values below 0.10, the coefficient estimate is presented in bold. The Wald test of exogeneity instrumenting for team (GRP\_MEM, GRP\_USE, GRP\_IMP, STID) is 26.21 and statistically significant with p-value below 0.01

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