"Networks of Green People"

: Dynamic Network Closure and Prosocial Behaviors in Online Communities

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ABSTRACT

There is a growing interest in designing incentives to foster "green" or *prosocial* behavior in environment sustainability. We show that online social network is conducive to energy saving behavior through social influence. Using data collected from online community Carbonrally.com, we show that slower growing groups perform better in energy reduction. In addition, we also show that the strength of ties and group characteristics that individuals belong to are important predictors of prosocial outcome. We present results and implication of our study.

[1] This is a student-authored paper with Professor Siva Viswanathan as principal advisor.

1. Introduction

In the "green" or sustainable environment context, there is a growing interest in fostering energy conscious behaviors among consumers with incentives. Offering price discounts or rebates for switching old appliances with energy efficient ones or reducing monthly home energy use has been met with some success, but the realized cost savings have not been significant enough for consumers to make a permanent behavioral change[2]. Instead, non-price interventions relying on social norms to affect individual behavior have gained more interest recently. For instance, OPOWER's pilot study on providing individuals with neighborhood usage for social comparison (Allcot 2010) and Oberlin College's program on displaying real-time energy use on websites for dorms to compete against each other (Petersen et al. 2005) both show that social influence may be more effective than economic incentives alone.

Of particular interest concerning social incentives for fostering *prosocial* behaviors is how online social networks promote visibility of individual action to others. For instance, a large network provides more opportunities to demonstrate "green" behavior to others in creating a positive image for oneself. In contrast, a small network may not have the same level of exposure but more frequent interactions with fewer members can help build a stronger relationship, resulting in a positive image. Maintaining close ties with other members becomes more difficult as networks get large in offline setting. However, the growth of Web 2.0 technologies and the explosion of online social networks have significantly increased the connectedness of individuals *as well as* their visibility among peers and friends. Therefore, it would be interesting, from a theoretical as well as practical perspective to understand how the different relational and structural aspects of an individual's social network influence their prosocial behaviors.

Specifically, this research study seeks to address the following questions:

1. How do the *structural* properties of an individual's social network impact her performance outcomes? For instance, are individuals central to a network more likely to outperform individuals in the periphery?

[2] Plan-It-Wise Energy Program conducted by Northeast Utility Company, http://www.cl-p.com/home/saveenergy/goinggreen/planitwise.aspx

Further, is an individual with a "closed" social network more likely to exert greater effort than an individual whose social network comprises of "structural holes"?

2. How do the *relational* aspects – the strength of ties – affect an individual's prosocial outcomes?
3. How do the *dynamic* characteristics of network affect individual performance? What interactions, if any, exist among size and density of networks over time?

Data used for this study are collected from Carbonrally.com, one of the fastest growing online communities for "green" or environmentally conscious users. Carbonrally provides a social networking platform that enables members to compete with one another by accepting challenges or activities that reduce carbon emissions. Members on Carbonrally.com can compete as individuals or as part of an online team. Members typically adopt "challenges" or specific tasks involving one-time or repeated engagements in energy-consumption reducing behaviors. Each challenge has a different level of difficulty and outcome, measured by the pounds of carbon dioxide (CO2) reduced. Once each task is completed, a member then posts the outcome on a personal web page visible for others to see. In addition, members may invite their friends to join and compete, either as an individual or as part of a team. Organizations including businesses, universities, and schools, among others, can form a private or public league to compete. The presence of these online networks makes Carbonrally an ideal research setting to observe how an individual's connections to other members in a social network affect her prosocial outcomes – specifically her ability to reduce carbon emissions. More specifically, we seek to understand how network closure and network size influence prosocial behaviors in online communities.

The online communities context is interesting given public interest in sustainability and the growth of Web 2.0 technologies such as Facebook and Myspace to potentially support collective action. This study extends the literature on network closure and community size by incorporating dynamic component of network structure; namely, how the growth rate of a network or community interacts with network density and size to affect prosocial outcomes.

We find that a slower growing online social network fosters prosocial behaviors. As members need sufficient time to cultivate relationships with each other, the ease of access to multitude of potential friends online may inadvertently reduce interaction and subsequently erode participation. We also find that controlling for growth rate, a high closure with large size network is positively associated with prosocial behaviors. Together, these findings indicate that given sufficient control on the rate of growth of an online community or network, information technology can sustain a larger social network to remain productive by fostering specific network characteristics. These findings relating to the impact of network characteristics on prosocial behaviors may also be potentially useful in rallying the masses for other collective action such as voting, volunteering, and public services.

The rest of the paper is organized as follows. Section 2 outlines related research that informs our theoretical arguments in the study. Section 3 describes the data, measures, and methodology, while Section 4 presents the results. Section 5 concludes with a discussion of the implications of our findings.

2. Theoretical Background

The growth of online social network spurred on by Web 2.0 technology has fueled new interest in how online communities can support *prosocial* behaviors, defined as a broad range of individual actions intended to benefit one or more people other than self – such as helping, comforting, sharing, donating, and cooperation (Trivers 1971; Batson 1998; Fehr & Fischbacher 2003). First, much of the extant research on online social networks in this context has focused on how firms can reduce costs by *crowdsourcing*, or leveraging online communities to provide support for operational activities such as customer service or product reviews. Less attention has been given to the role of online networks and communities in fostering public service tasks such as voting, volunteering, and energy conservation. Second, prior research on prosocial behaviors has primarily focused on a fixed set of internal beliefs such as values, personal norm, and awareness as rationale for participation (Liebrand et al. 1986; Stern and Dietz, 1994, Batson 1998)**.** These studies explain underlying individual attitudes but do not adequately prescribe how to induce prosocial behaviors under repeated interaction at a dyadic or collective level. This study primarily draws from the social networks literature to examine how social incentives such as signaling a positive image induce individuals to engage in prosocial behaviors – specifically, energy saving behaviors of individuals in online communities.

2.1. Network perspective on prosocial behaviors

Network perspective on prosocial behaviors provides a useful framework to explain how connected individuals can influence each other. By definition, there are at least two actors – "self" and "other" – to confer and receive benefit, respectively, and structural aspects of social network can serve as effective mechanisms to facilitate as well as constrain individual behavior. For instance, *network closure* describes how everyone in a closed network is connected to one another that it is difficult to escape the notice of others (Burt 1992). Therefore, if one values the notice of others in a network, then high network closure enhances members to engage in socially acceptable behaviors while refraining from any deviant behaviors and risk possible exclusion from the group.

Two competing views ascribe both positive and negative outcomes associated with increased network closure. First, Coleman (1988) theorizes that high closure, where individuals share many friends in a community, facilitates cooperative behavior. For instance, using data collected in Peru, Karlan et al. (2009) infer that a local network of friends can secure informal financial transactions through *social collateral* – that is, an individual member refrains from selfish behavior such as defaulting or not repaying loans, for fear of losing friendships that outweigh the reward of keeping the money for her.

According to Coleman, social capital is created by strongly interconnected individuals who facilitate social sanctions to preserve group unity. For instance, any member who exhibits deviant behavior would be swiftly punished or ostracized from the rest of the members. Social norm develops based on similarity of member composition in either individual characteristics (Axelrod 1981) or observed behaviors (Cialdini and Trost, 1998). These groups with similar characteristics have found to exhibit a higher level of prosocial behaviors (Hoffman et al. 1996; Eckel and Grossman 1998, 2001; Gneezy et al. 2003).

In contrast, Burt (1995) argues that low closure provides a greater access to information and social learning. He posits that loose network of individuals who are "structural holes" – those who bridge disconnected groups of individuals – perform better by infusing new information obtained from diverse set of individuals unavailable in a static, closed network. Notable concepts developed by Granovetter's strength of weak ties (1973), Freeman's betweenness centrality (1977), and Burt's structural hole measures (1992) all emphasize the role of a central agent who appropriates a flow of information to peripheral members for decision making and subsequent action. Therefore, a network with greater opportunity for social learning provides a member awareness of what to do in a prosocial context while removing uncertainty about who is participating.

2.2. Network Closure, Size, and Growth

Relative benefit of high or low closure depends on the community size (Allcot 2007), as well as the value of the resources being exchanged (Karlan et al. 2009). A closed network with smaller community size provides a better social control of agent behaviors and enables exchange of valuable assets such as material or monetary goods. A low closure or open network with large community size presumably exposes members to observe and acquire more information for better social learning. Although ideal network structure would be high closure with large community size, maintaining such structure may be difficult due to interaction between network closure and size.

At first, it seems community size is positively correlated with network closure (Gould 1993). For instance, as more individuals join a community, probability of forming a relation among members increases. However, more frequent interactions also lead to conflict between members or competing groups vying for membership of existing individuals, thereby reducing size (Tajfel 1982).

Finally, how a social network increases or decreases in size over time depends on the role of a central agent controlling information flow to peripheral members. For a network to grow, interactions among members may be a prerequisite before any recruiting new member takes place. A central agent plays a critical role in connecting members and someone peripheral may have fewer chances to connect with others as her distance from the central agent increases. Thus, a central agent can play an important role in the growth of network over time.

2.3. Structural Characteristics of Network and Member Participation

In the energy saving context, a rationale for member participation depends on the network size being sufficiently large enough as well as the structural position and role of network members. For example, observing too few participants or too many participants may influence a non-participant to remain inactive or free-ride on others' contribution**.** Assessing the network size and observing member contribution then depends on the "node" or structural position she occupies. Therefore, both network and node properties are important in understanding member participation.

Prior research on prosocial behaviors has examined the role of image motivation or signaling in fostering prosocial behaviors (Ariely 2009). Stemming from signaling reputation or wealth (Geanakoplos et al. 1989; Rabin 1993; Glazer et al. 1996), experimental studies have shown that maintaining a good "image" or reputation serves as strong incentives (Hoffman et al. 1994; Hoffman et al. 1996). For instance, Andreoni (1988) showed that signaling wealth may be primary motivators to explain giving donation to charity. Various experimental studies have replicated the findings that image motivators are important drivers of prosocial behaviors (Camerer 1996; Hoffman et al. 1996; Soetevent 2004; Andreoni and Petrie 2004; Dana et al. 2006; Koch and Normann 2008; Ariely 2009). In the context of a network or community, an individual's position in the network influences the benefits she derives from such signaling. A peripheral member who occupies a network position far from a central agent might be more prone to free-riding. In contrast, a central member, by virtue of her connections, is likely to benefit more from the visibility of her prosocial actions. Network characteristics such as closure, size, and structural position of members are thus, likely to influence prosocial behaviors. Online communities in particular, can enhance prosocial behaviors by simultaneously reaching out to many members and yet sustain close ties through feedback (Constant et al.1996; Moon and Sproull 2008). The potential to create and sustain a large network with high closure is much higher than in an offline context. Our study will examine if high network closure is indeed positively associated with prosocial behaviors. We are also interested in understanding how network size interacts with network closure to promote prosocial behaviors. Lastly, we will also examine how the rate of growth of a network affects these outcomes.

3. Data and Analysis

As noted earlier, the primary dataset for this study is provided by Carbonrally.com – one of the fastest growing and most active online communities for "green people". Carbonrally has been in existence for about two years and currently has 30,000 members, of which approximately 20,000 are active. The proprietary dataset from Carbonrally contains extensive information about individual participants, the details of the challenges taken by them, the outcomes of the challenges, communication among members within a group, etc. Personal information includes profile, location, contact information, tenure, team affiliation (if any), and detailed information on activities performed. Activity-related information includes task difficulty, task outcome, duration, and date of commencement. Detailed information (de-identified data) on messages exchanged between members, broadcast to team members, and invitations to join as well as click rates, are available through separate email server logs. As noted earlier, our goal is to understand how individual outcomes are influenced by different aspects of a member's social network. In addition to information on individuals, groups, organizations, and their activities, we have detailed data on the social networks on members on Carbonrally.com. There are multiple networks on Carbonrally.com. In addition to friendship, group, and league networks, the email server logs also enable us to define the strength of the links based on the messages exchanged between the participants. The preliminary analyses indicate low degree-centrality as well as low betweenness-centrality, suggesting the presence of highly decentralized networks.

3.1. Description of Data

The data set is panel data consisting of individual level activities reported for "challenge" or task accepted and completed during 2007-2010. There are approximately 128,000 observations of challenge activities. Since many users perform activities one time and often exit the online community, we have aggregated the activities to monthly total per individual for 30 time periods and 19,835 users. We have reduced the data set to U.S. population, although users can connect from anywhere in the world. After aggregating and removing non-U.S. members, a final sample size consists of 34,575 observations. Table 1 shows a descriptive statistics for our sample.

3.2. Measures

The description of the measures is listed in Table 2. The dependent variable of interest is *CO2*, which is a monthly total of CO2 reduced (lbs) for each individual. This measure represents a member's total energy saving activities performed in a given time period and affects both personal and group performance on leader board. The distribution of CO2 reduced is positively skewed and log-transformed to approximate normally distributed continuous variable.

3.2.1 Network Measures

We use UCINET software package to calculate network properties of participants in Carbonrally from existing relations among members. A relation or "ties" between two members are subsequently used to derive and calculate individual or "node" as well as group properties. For instance, node centrality measure such as *degree centrality* simply counts the number of ties a member has with other members, whereas *density*, which is a ratio of the number of actual ties present to the potential number of ties within a group, captures how closely members are tied to one another. These measures help us test our propositions, namely how the *relational* and *structural* aspect of a social network influence individual's decision to engage in prosocial behaviors. In summary, we derive several network measures – *degree, constraint*, and *density* –our main independent variables that predict prosocial outcomes, the amount of CO2 reduced by an individual.

First, we define any two members as being related if one was referred to, or recruited by, another to join Carbonrally. The binary variable *Referred* captures whether a relationship or tie exists between any two members on Carbonrally. Joining an online community through referral predicts future participation level of members (Hahn 2008) and forms a basis of social network in our analysis. Not all members were referred (37% of all members), and some might have joined on their own. Using the referral network, we capture several network measures for each time period to test how dynamic changes in network characteristics affect performance outcome related to prosocial behaviors.

ucomments is another measure of relatedness between any two members and is a count of the number of messages a member left to another member on her web page and proxies the level of recurring interactions between members.

We use two node centrality measures to help us identify a central versus a peripheral participant and help explain how structural position of individuals affects prosocial behaviors. As mentioned before, degree centrality is most commonly used measure of capturing a number of friends and represents how central a member is to others. Ranges of degree centrality is between 0 (those who did not refer anyone) to 335.

We also use a structural hole measured called *Constraint*, proposed by Burt (1992). According to Burt, structural hole captures a potential brokerage opportunity an individual has within a network. The values of *Constraint* are continuous and reverse coded between ranges of 0 to 1. Lower constraint value implies a member is typically a bridge to information flow to many members, whereas a high constraint value means that there are many redundant ties embedded in network and lowers the bridging value of an individual.

Network *density* is a proxy for network closure (Coleman 1988), i.e., how everyone in a closed network is connected to one another as described earlier. Lastly, we use two other measures to detect change in network properties over time. *Size* measures cumulative total of team members for each time period. Since the distribution of team sizes are skewed, this variable was log transformed. *Growth* captures a rate of change in team size between time periods.

3.2.1 Control Variables

We need to capture several control variables for validity of our analysis and remove any potential bias in interpreting our results. First, we control for differences in difficulty of the challenges that members undertake which affects the amount of CO_2 reduced. For example, a peripheral or free-riding member may choose challenges with lower CO_2 rating and undertake fewer challenges, whereas a central member may undertake higher rated challenges and perform more often. We use *CO_2 Rating*, that averages the CO_2 rating of each challenge taken for each time period, as a proxy for the difficulty of a challenge undertaken by an individual.

Next, the *User Type* – where each member indicates whether she is: (1) in junior high or high school, (2) college or university, (3) company, or (4) none of the above - serves as a proxy for their age and education. Each type is captured as dummy variables and included in our analysis. Finally, *Leader* captures a social role of a member who derives reputational payoffs by accepting membership requests, recruiting potential members, and encouraging others to contributes.

Key summary statistics are shown in Table 1. On average, each individual remains active for 1.74 months, or roughly equivalent to 52.2 days. During this period, a member reduces on average 112 lbs of CO2. As mentioned earlier, average network density for teams is low (~0.20) representing decentralized network. Although not shown, approximately 70% of all members choose to join a team. Only about 7% of all members take on a team leader role. A simple ANOVA on team and leader dummy variables show higher *CO2* performance outcome, on average 31% increase for joining a team and 35% for being a leader, respectively.

3.3. Methodology and Analysis

As mentioned earlier, our primary goal is to test how structural (*density*, and *size*) and relational (*degree* and *constraint*) measures of a member's social network affect her prosocial outcomes (*CO2)*. We also want to test how these measures vary over time to understand how repeated interactions of members affect prosocial tendencies.

A panel regression (Table 3) was used our main specification model (Equation 1). A software package STATA was used to code and run several regression models to address potential endogeneity concerns (discussed in the following section). Since theory predicts a member's decision to participate depends on both individual and group influences, a random effects model with robust standard errors was chosen as the appropriate model. In addition to the variables described earlier, we include *Density*Size* to specify interaction between network density and size (Karlan 2009). *Growth* captures growth of the network over time.

Lastly, a set of variables help control for potential biases arising from confounding or omitted variables. A lagged variable of *ln(CO2)* for one time period was included to account for possible autocorrelation between time periods.

$$ln(CO2)_{it} = \alpha + \beta_1 Referred_i + \beta_2 Ucomment_{it}$$

$$+ \beta_3 Degree_{it} + \beta_4 Constraint_{it} + \beta_5 Density_t + \beta_6 ln(Size)_t +$$

$$\beta_7 Density{*}Size_t + \beta_8 Growth_t + \beta_9 ln(CO2)_{it-1} + \beta_{10} CO2\ Rate_{it} + \beta_{11} Leader_i + \beta_{12\text{-}14} User\ Type_i$$

$$+ \varepsilon_{it}; \quad (1)$$

We note that a positive coefficient on *Constraint* depicts that on average, more constrained members or redundant ties in a network, higher level of CO2 is expected. The primary test for online communities enabling larger community with high closure is given by *Density*Size*, where the interaction term represents by how much the effect of *Density* on CO2 is changed when considering change in network *Size*.

4. **Results**

Table 3 presents the results of the panel regression analysis with random effects. Column 1 presents the results of the benchmark OLS model. We find that *ucomment* has a positive and significant effect, which indicates that members who interact in a social network tend to behave more prosocially. The value of additional comment exchanged between members in a month increases contribution level of CO2 by 3-4%. This suggests that online social networks have a potential to foster green behaviors.

Our primary interest lies in how network properties influence prosocial behaviors. First, relational position of individuals, measured by *Degree* and *Constraint* centrality, is not statistically significant. However, structural characteristics such as *Density* and *Size* are statistically significant but negatively correlated with CO2 reduction. More dense networks and large networks decrease prosocial tendencies. Although these results seem somewhat puzzling at first, examining the interaction term is revealing. We find that the effects of density and community size on prosocial behaviors is different at different levels. At low densities, a decrease in community size is associated with positive performance, whereas at high density an increase in community size is associated with positive performance as measured by CO2 reduction. Lastly, a negative and statistically significant *Growth* indicates that slow growing communities may be better off in sustaining CO2 reduction efforts. Together these findings indicate that online communities may promote green behaviors only under conditions which members are allowed to interact with other members at a slow enough pace, so that rapid growth in team size does not prevent reduction in performance.

These preliminary observations seem interesting but our model has two potential variables whose observed factors or endogeneity may bias our results. Structural measures of network such as *Density* and *Size* may be endogenous with performance outcome. In addition, individual challenge selection, measured by a single variable *CO2 Rate* may be endogenous with the dependent variable as well. To remove endogeneity due to selection bias as well as omitted variables from these two sets of variables, we take instrumental variable (IV) approach, developed by recent advances in econometrics literature (Woolridge 2007). We outline our selection of instrumental variable and make three modifications to our original model. Columns 2 show our IV results. We were unable to find a suitable instrument for *CO2 Rate*, and a future study will attempt to identify one.

First, there is a potential selection bias associated with network closure, *density*. Those who are more prosocial may be more likely to connect with other members, whereas self-interested individuals may choose to perform challenges on their own. To address this endogeneity issue we use a member's location – State – as a set of instrumental variables. There are fifty states represented in our data set, so we use 49 dummy variables. Many members in Carbonrally join together as a group. For instance, company teams like Seventeen or NBC use Carbonrally to promote in-company green behaviors, whereas high school or college teams like Notre Dame join together as well. They are usually located in the same vicinity, so these IV's may predict network density. However, location does not readily correlate with CO_2 reduction, so the IV's satisfy exogeneity and exclusion condition on a theoretical level. Alternatively, similar arguments can be made for city location as instrumental variables for more granularities, but there are 4904 cities represented in our sample which can potentially reduce number of observations required to run our model. The validity of these many weak instrumental variables can be tested using an F-statistic of greater than 10 in the first step of the two-step procedures (2SLS). These procedures are repeated for *Size* as well. Equation 2 shows a formal model of the first step, and the predicted values are used to run a second step procedure.

$$(Density_{,}\ ln(Size))_t = \alpha + \beta_1 Referred_i + \beta_2 Ucomment_{it}$$

$$+ \beta_3 Degree_{it} + \beta_4 Constraint_{it} + \beta_5 Growth_t + \beta_6 ln(CO2)_{it-1} + \beta_7 CO2\ Rate_{it}$$

$$+\beta_8 Leader_i + \beta_{9\text{-}11} User\ Type_i + \beta_{12\text{-}60} State[1\text{-}49]_i + \varepsilon_{it};\ \ (2)$$

The IV approach show similar results as the OLS model, with the exception of *Constraint*. Results underscore the importance of social context in prosocial behaviors. The coefficient of structural measures *Density* decreases from -0.641 to -2.157, representing about three-fold change. The coefficient for *Size* does not change much, perhaps indicating that network closure is more important in prosocial behaviors than community size alone.

5. Discussion

This research study set out to test how network closure affects prosocial behaviors. Leveraging from two competing hypotheses in sociology literature, both Coleman's network closure and Burt's structural hole views were considered and tested. Before we discuss the implication of our results, several limitations must be stated.

First, this study uses data collected from online communities and does not directly measure individual characteristics such as values, personal norms, and awareness to prosocial behaviors. In addition, the focus of this study is not on how personal preferences affect prosocial behaviors but rather how social influence affects such behavior. However, there may be unobserved factors that could lead to biases. Our ongoing work includes a survey to test this possibility. We make assumption that members report energy saving behavior truthfully, but we cannot verify member activties. Although there is no immediate reward for falsely reporting individual activities, a potential bias from gaming behavior could challenge the validity of our results. A future study using field experiment or controlled experiment in a laboratory setting may uncover if there is sufficient incentives for individuals to cheat in prosocial behaviors.

Second, our choice of defining relation based on referral may not fully capture ongoing interaction between members in a social network. A more useful metric may be internal or external messages exchanged among members. A method of communication captured by the internal messaging system shows that most of the messaging is communicated through team message, so a peer-to-peer message exchange is somewhat limited. A future study will incorporate message exchange to account for strength of tie to construct valued network.

Based on the results shown in this study, our main implication is that for energy saving context in online communities, controlling the growth of community and cultivating stronger relationships between members may be more important than simply recruiting as many members as possible. Although the ubiquity of social network makes recruiting and collecting members into a group easy, such behavior may not lead to desired outcome. Given enough social control, online communities can enable a larger network of individuals to be maintained.

Although inconsistent across our model, another interesting result shows that *Referred* members exhibit lower performance outcome than non-referred members. Unlike in online communities where members exchange information or provide relational support, prosocial context draws members who are mostly unwilling participants. An implication of this result is that incentives need to focus an average member whose initial preference is to free-ride.

Generalizing this result to other collective action context such as voting, volunteering, and charity contribution, cooperative behavior implies that social control may be more conducive to collective outcome than encouraging individuals to act freely. This has interesting policy implications whether to offer rewards or punishment for desired behavior. Our results suggest that online communities may need to consider designs that limit a central person such as leader power to decide who to accept as a member and further control or even censor communication between members to insure group unity.

References

Allcott, H, Karlan, D, Mobius, M., Rosenblat, T., and Szeidl,A. (2007), “Community Size and Network Closure,” American Economic Review Papers and Proceedings, 97, 80–85.

Allcott, H (2009), “Social Norm and Energy Conservation, MIT Center for Energy and Environmental Policy Research, Working Papers

Andreoni, J., (1988). Why free ride? Strategies and learning in public goods experiments. Journal of Public Economics 37, 291– 304.

Andreoni, J.and Petrie, J. (2004): “Public Goods Experiments Without Confidentiality: A Glimpse Into Fund-Raising,” Journal of Public Economics, 88, 1605–1623.

Ariely, D., Bracha, A, and Meier, S. (2009), “Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially”, Mimeo,

Axelrod, R. and Hamilton, W. (1981), “The Evolution of Cooperation”, Science, Vol. 211, 1390-1396.

Batson, D. (1998), Altruism and Prosocial Behavior, In D. Gilbert, S. Fiske, & G. Lindzey (Eds.) ‘‘The handbook of social psychology, (4th edition) vol. 2’’, New York: McGraw-Hill, Chapter 23.

Burt, Ronald S.(1995), Structural Holes: The Social Structure of Competition (Cambridge, MA: Harvard University Press,).

——, “The Network Structure of Social Capital,” in Research in Organizational Behavior, No. 22, R. I. Sutton and B. M. Staw, eds. (Amsterdam: Elsevier Science, 2000).

Cialdini, R.B., & Trost, M.R. (1998). “Social influence: Social norms, conformity, and compliance.” In D. Gilbert, S. Fiske, & G. Lindzey (Eds.) ‘‘The handbook of social psychology, (4th edition) vol. 2’’, pp. 151-192. New York: McGraw-Hill.

Coleman, James S., “Social Capital in the Creation of Human Capital,” American Journal of Sociology, 94 (1988), 95–120.

——, Foundations of Social Theory (Cambridge, MA: Harvard University Press, 1990).

Constant, D., L. Sproull, S. Kiesler. 1996. “The kindness of strangers: The usefulness of electronic weak ties for technical advice”. Organization Science. 7(2) 119–135.

Dana, J., Cain, D. and Dawes, R. (2006): “What You Don’t Know Won’t Hurt Me: Costly (But Quiet) Exit in Dictator Games,” Organizational Behavior and Human Decision Processes, 100, 193–201.

Eckel , C., and Grossman, P.(1998), “Are Women Less Selfish Than Men?: Evidence from Dictator Experiments”, The Economic Journal, Vol. 108, No. 448 (May, 1998), pp. 726-735

____, (2001) “Chivalry and Solidarity in Ultimatum Games”, Economic Inquiry, Vol. 39, No.2, 171-188

Fehr, E. and Fischenbacher, U. (2003), “The nature of human altruism”, Nature, 425, 785-791

Freeman, Linton C. (1977), A set of measures of centrality based on betweenness. Sociometry 40:35-40.

Geanakoplos, J., Pearce, D., and Stacchetti (1989): “Psychological Games and Sequential Rationality,” Games and Economic Behavior, 1, 60–79.

Glazer, A., and Konrad, K. (1996): “A Signaling Explanation for Charity,” American Economic Review, 86, 1019–1028.

Gould, R. (1993), “Collective Action and Network Structure”, American Sociological Review, Vol.58, 182-196.

Granovetter, M, (1973), “The Strength of Weak Ties,” American Journal of Sociology, 78 1360–1380.

Hahn, J., Moon, J.Y., and Zhang C. 2008. Emergence of New Project Teams from Open Source Software Developer Networks: Impact of Prior Collaboration Ties, Information Systems Research (19:3), 369-391.

Harbaugh, W., (1998), “The prestige motive for making charitable transfers”. American Economic Review 88 (2), 277– 282.

Hoffman, E., McCabe, K. and Smith, V. (1996). “Social Distance and Other-Regarding Behavior in Dictator Games”, The American Economic Review, Vol. 86, No. 3. 653-660

Karlan, Dean, Markus Mobius, Tanya Rosenblat, and Adam Szeidl (2009). “Trust and social collateral”. Quarterly Journal of Economics, 124, No. 3.

Liebrand, W. B. G., Jansen, R. W. T. L., Rijken, V. M., & Suhre, C. J. M. (1986). “Might over morality: Social values and the perception of other players in experimental games”. Journal of Experimental

Social Psychology, 22, 203–215

Macy, M. (1991), “Chains of Cooperation: Threshold Effects in Collective Action”, American Sociological Review, 56, 730-747.

Moon and Sproull. 2008. “The Role of Feedback in Managing the Internet-Based Volunteer Work Force.” Information Systems Research, 19(4), 494-515.

Petersen, J., Shunturov, V., Janda, K., Platt, G., and Weinberger, K. (2005), “Does Providing Dormitory Residents with Feedback on Energy and Water Use Lead to Reduced Consumption?”, Proceedings, Greening the Campus VI, Ball State University, Muncie, Indiana.

Rabin, M. (1993), “Incorporating Fairness into Game Theory and Economics”, The American Economic Review, Vol. 83, No. 5, 1281-1302.

Soetevent, A. (2005): “Anonymity in Giving in a Natural Context—A Field Experiment in 30 Churches,” Journal of Public Economics, 89, 2301–2323

Stern, P. C., & Dietz, T. (1994). “The value basis of environmental concern”. Journal of Social Issues, 50, 65–84

Tajfel, H. (1982), “Social Psychology of Intergroup Relations”, Annual Review of Psychology, 33, 1-39.

Trivers, R. (1971), “The Evolution of Reciprocal Altruism”, The Quarterly Review of Biology, 46, 35-57.

Appendix

Table 1: Descriptive Statistics

Variable	Obs (N)	Mean	Std. Dev.	Min	Max
ln(CO2)	34601	3.975533	1.35257	-2.525729	7.665753
CO2 Rating	34601	34.29854	34.31737	0.4	248
Leader (1=Yes)	34601	0.071443	0.2575671	0	1
Degree	34601	0.561111	2.806387	0	335
Constraint	34601	0.3420634	0.4659798	0	1
Density	21822	0.2067195	0.3223938	0	1
ln(Size_Cum.)	34601	5.883353	2.743175	0	8.881142
Growth	24055	0.3245397	0.4034558	0	0.9929578
Referred	34601	0.331985	0.470932	0	1
Ucomment	34601	0.072194	2.166879	0	325

Table 2: List of Variables

Name	Description	Level
<u>*Dependent Variable*</u>	_	_
ln(CO_2)	Monthly total of CO_2 Reduced	Individual
<u>*Independent Variable*</u>		
Network Measures		
Referred	Whether a member has been referred by another member	Individual
Ucomment	Number of messages sent to another member	Individual-Individual
Node Properties:	*Node Centrality Measure:*	*Node Centrality Measure:*
Degree	Number of friends	Individual
Constraint	Structural Hole - Constraint	Individual
Group Properties:	*Group Centrality Measure:*	*Group Centrality Measure:*
Density	Group Density	Team
ln(Size)	Cumulative Total of Team members	Team
Growth	Change in Cum. Total of Team Members	Team
Control Variables		
CO_2 Rating	Average CO_2 reduced per task	Individual
Leader (1=Yes)	Whether a member is a team leader	Individual
User type (1-4)	1=Misc; 2=Junior High School or High School; 3=College or University; 4=Company	Individual

Table 3: Panel Regression

Dependent Variable: ln(CO2)	OLS b/se	IV(Density & Size only) b/se
Referred	-0.105	-0.149*
	(0.069)	(0.059)
Ucomment	0.037**	0.036**
	(0.009)	(0.005)
Degree	0.004	0.000
	(0.004)	(0.003)
Constraint	-0.010	0.141*
	(0.068)	(0.067)
Density	-0.641**	-2.157**
	(0.097)	(0.426)
ln(Size)	-0.075**	-0.096**
	(0.007)	(0.022)
Density*ln(Size)	0.095**	0.549**
	(0.029)	(0.140)
Growth	-0.120**	-0.081*
	(0.023)	(0.036)
ln(CO2[t-1])	0.042**	0.034**
	(0.007)	(0.006)
CO2 Rate	0.021**	0.021**
	(0.000)	(0.000)
Leader	0.404**	0.761**
	(0.075)	(0.140)
User Type (JHS/HS)	0.068**	0.061
	(0.026)	(0.036)
User Type (College/University)	0.064*	0.076*
	(0.031)	(0.031)
User Type (Company)	0.021	0.056
	(0.039)	(0.045)
_cons	3.629**	3.702**
	(0.059)	(0.125)
R-Squared	0.32	0.30
N	18,857	18,857