The Influence of Network Structure and Prosocial Cultural Norms on Charitable Giving: A Multilevel Analysis of Movember's Fundraising Campaigns in 24 countries

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Abstract

This study examines how the interplay between an online campaign's network structure and prosocial cultural norms in a country affect charitable giving. We conducted a multilevel analysis that includes Twitter network and aggregated donation data from the 2013 Movember fundraising campaigns in 24 countries during 62 campaign days. Prosocial cultural norms did not affect the relationship between network size and average donations raised, nor did they affect the relationship between network centralization and average donation amount. Prosocial cultural norms did affect the relation between network density and average donations raised. However, this effect was negative and contrary to our expectation.

Keywords. Cultural norms, Collective action, Charitable giving, Communities, Social networks, Campaigns, Social media.

INTRODUCTION

"Under which conditions do people take action that benefits others?" is one of the fundamental questions in social science. Thus far, research has discussed two key factors that explain variation in such (collective) prosocial behavior: social networks and prosocial cultural norms (Bekkers, Völker, Van der Gaag, & Flap, 2008; Bekkers & Wiepking, 2011). In the literature, prosocial behavior is often studied as a product of social pressure and opportunities made available through social networks, whereas the motivations for prosocial behavior are studied in terms of cultural norms and values (Bekkers & Wiepking, 2011; Ruiter & De Graaf, 2006). To date, however, most studies have separately examined the influence of either network structure or norms on prosocial behavior (Bekkers & Wiepking, 2011; Ruiter & De Graaf, 2006; Bekkers & Schuyt, 2008; Wang & Graddy, 2008).

Consequently, this study's first contribution to the literature is through the examination of how prosocial cultural norms modify the relationship between a campaign's network structure and prosocial behavior. Social networks may facilitate prosocial behavior because network members monitor and possibly sanction behavior of other network members (Burt, 2000; Coleman, 1990), which may increase the chance that network members are asked to contribute – for instance by charitable giving (Bekkers & Wiepking, 2011). In the sociological literature, it remains to be determined whether such network closure can independently lead to more donations or whether the normative pressure from prosocial cultural norms is required to convince network members to contribute to prosocial requests from their social network. For example, people may be more responsive to prosocial requests when their country has strong prosocial cultural norms. In sum, our study responds to calls for research on whether and how network structures and the prosocial cultural norms of countries interact (Bekkers & Wiepking, 2011).

This study's second contribution to the literature is through its examination of how prosocial cultural norms and *online* social networks jointly stimulate (collective) prosocial behavior. Digital media, such as social networking sites, are increasingly employed by fundraising organizations to promote (collective) prosocial behavior, e.g., generating funding for health research (Chou, Prestin, Lyons, & Wen, 2013; Maher et al., 2014; Wehner et al., 2014). However, little is known about how prosocial cultural norms and online social networks jointly stimulate (collective) prosocial behavior (Saxton & Wang, 2014; van Leeuwen & Wiepking, 2013). An emerging body of sociological research on online collective action argues that the low costs, speed, scale, and connectivity of digital media may reduce the need for the formal, centralized organization of collective action (Bennett & Segerberg, 2012; Bimber, Flanagin, & Stohl, 2005; Lupia & Sin, 2003; Saxton & Wang, 2014). Empirical research on large-scale campaigns, however, indicates that online mobilization can be also highly centralized (González-Bailón & Wang, 2016). Therefore, more research is required to clarify the role of online network structures in the mobilization of collective action aimed at (collective) prosocial behavior. Social network analysis offers an unobtrusive method for studying the underlying networks of large-scale movements and national campaigns (González-Bailón, Borge-Holthoefer, Rivero, & Moreno, 2011; González-Bailón & Wang, 2016).

Consistent with both of the above-mentioned contributions to the social network literature, our study's research question is as follows: *"To what extent and how do the prosocial cultural norms of countries modify the relationship between network structure and average donation amount within countries during a Twitter-based fundraising campaign?"* The empirical setting is the global Movember campaign of 2013. In that year, Movember fundraisers collected approximately 147 million US dollars for male cancer and mental health research. We use data varying over time from the Movember 2013 Twitter campaign in 24 countries[1] to analyze the extent to which prosocial cultural norms during the 62 days of the online campaign modified the relationship between network structure and donations raised.

THEORY AND HYPOTHESES

The general premise of our study is that (collective) prosocial behavior, such as charitable giving, in a country is the outcome of prosocial opportunities made available through the network structure in which members are embedded and the normative pressure – stemming from the country's prosocial cultural norms – to perform this prosocial act (e.g., donating) (De Graaf et al., 2004; Hedstrom, 2005; Ultee & Luijkx, 1998). Below, we derive hypotheses by focusing on the opportunities stemming from social networks and the normative pressure – provided by prosocial cultural norms – to identify and act upon prosocial opportunities.

Pressure and opportunities from social networks

The structure of social networks is considered an essential driver of the organization of collective action such as charitable giving (Wang & Graddy, 2008) or protesting (González-Bailón et al., 2011; Gould, 1993; Marwell, Oliver, & Prahl, 1988). Specifically, network closure, which represents how strongly nodes are interconnected, is considered a driver of collective action (Marwell et al., 1988), such as (collective) prosocial behavior (Bekkers et al., 2008; Brown & Ferris, 2007; Burt, 2000; Coleman, 1990). However, empirical research on the indicators of network closure, such as membership in voluntary organizations, does not indicate a strong relationship between network closure and volunteering or charitable giving (Bekkers & Veldhuizen, 2008; Brown & Ferris, 2007). A more detailed

[1] We recognize that Hong Kong is officially an autonomous administrative region of the People's Republic of China. However, we label it as a country in this article to make the levels of analysis clear.

analysis of network closure's sources, such as network size, density and centralization, may explain under what conditions a network structure leads to (collective) prosocial behavior (Allcott, Karlan, Möbius, Rosenblat, & Szeidl, 2007; Burt, 2001; Putnam, 2000).

Network size represents the number of nodes in a social network, i.e., the number of participants in a campaign. On the one hand, the average donation amount might be lower in larger campaign networks due to "free rider-effects" (Olson & Caddell, 1994). In large groups, unmotivated participants tend to refrain from making substantial contributions while still benefiting from the common goal. The public nature and low costs of participation via digital media attract these free-riders, often referred to as slacktivists (slack activists) (Barberá et al., 2015; Lewis, Gray, & Meierhenrich, 2015). The complexity of monitoring large social networks may reduce the social pressure on these slacktivists to give a substantial donation to the campaign (Bekkers & Wiepking, 2011). On the other hand, network size may also stimulate collective action, especially in online networks. Large networks provide the opportunity to activate more donors who are solicited by other network members, as more individuals are (indirectly) connected (Bekkers & Wiepking, 2011; Saxton & Wang, 2014). Moreover, the low costs, transparency, and high speed of digital media may decrease the risk of participants benefitting from the collective action without contributing (free-rider problem), as participants can donate small amounts of money without substantial transaction costs, and individual contributions are more easily monitored (Bennett & Segerberg, 2012; Bimber et al., 2005; Lupia & Sin, 2003). Following the recent insights into the positive effects of network size on charitable giving, we test the following hypothesis:

H1: The higher the number of nodes in the social network of a country's online health campaign on a particular campaign day, the higher the average donations per campaign day in that country.

Network density refers to the ratio of social ties in the network and the number of ties that are mathematically possible in the same network. Social ties provide an important opportunity for collective action (Gould, 1993; Marwell et al., 1988) because they play a key role in recruitment and mobilization processes (Tilly, 1978). Network density, for example, may increase the opportunity to collect donations by stimulating the diffusion of social information among network members. Although some studies suggest that bridging social networks – i.e., those with a low density – stimulate charitable giving (Wang & Graddy, 2008), most studies indicate that charitable giving is rather strongly related to social pressure from networks with high density (Bekkers et al., 2008; Bekkers & Wiepking, 2011). Hence, we propose:

H2: The higher the density of the social network of a country's online fundraising campaign on a particular campaign day, the higher the average campaign donations per campaign day in that country.

Network centralization refers to how central the most central node of the network is. Highly centralized networks have a few actors, such as opinion leaders, with whom most participants have ties (Diani, 1997). Network centralization is a source of network closure, as central actors connect most of the participants within the network. Several scholars argue that network centralization stimulates collective action by providing an opportunity structure for mobilization (?) (Marwell et al., 1988). A highly centralized campaign network can thus provide incentives for participants and central actors to coordinate collective action and prevent free-riding behavior (Ganley & Lampe, 2009; Marwell et al., 1988). However, other scholars argue that the use of digital media for the organization of collective action diminishes the importance of network centralization in providing opportunity structures (Bennett & Segerberg, 2012; Bimber et al., 2005; Castells, 2002; Lupia & Sin, 2003). The central claim of these scholars is that digital media decrease the marginal costs of collective action for organizers and participants. In this way, digital media enable so-called *connective action* for large numbers of people, and they do so without a centralized mobilizing structure (Bennett & Segerberg, 2012). Following the insights from connective action research, we expect:

H3: The higher the centralization of a country's online fundraising campaign on a particular campaign day, the lower the average campaign donations per campaign day in that country.

Prosocial cultural norms as normative pressure

Inhabitants of a country may be motivated to donate to a campaign organization when they are convinced of the campaign's cause (Andreoni, 2006). In general, inhabitants with strong prosocial motivations are more likely to donate to a cause (Bekkers et al., 2008; Farmer & Fedor, 2001). Prosocial motivations are embedded in the prosocial norms of a culture. Specifically, researchers note that *descriptive norms*, i.e., “what most inhabitants do”, may influence network members to behave similarly (Cialdini, Reno, & Kallgren, 1990). Consequently, collective action aimed at prosocial outcomes may vary among countries that differ in their prosocial cultural norms. Hence, we propose that prosocial cultural norms foster charitable giving in a campaign:

H4: The higher the level of prosocial cultural norms in a country, the higher the average donations per campaign day in that country.

Prosocial cultural norms motivate network members to respond to prosocial solicitations

We began by stating our most general premise, namely that (collective) prosocial behavior is the outcome of two forces: first, social pressure and opportunities from social networks that solicit for donations, and second, the prosocial cultural norms in a country, which exert the normative pressure to act according to the request (De Graaf et al., 2004). After all, network structures that provide opportunities to donate may be ample, but if there is no conviction to donate among social network members, people will not donate. This argument implies that opportunities may not have automatic consequences; social networks will exert stronger pressure for (collective) prosocial behavior in *combination* with stronger cultural norms.

Prosocial cultural norms provide network members with the motivation to respond to prosocial solicitations in their networks. Following the Political Mediation theory (Amenta, Caren, Chiarello, & Su, 2010), we argue that social network members that experience stronger prosocial cultural norms in their country are more likely to recognize and exploit the prosocial opportunities that their social networks offer. Hence, we propose that prosocial cultural norms reinforce the relationship between network structure and charitable giving in a campaign:

H4a: The higher the prosocial cultural norms, the stronger the association between the network size of a country's online fundraising campaign and average donations per campaign day in that country.

H4b: The higher the prosocial cultural norms, the stronger the association between the network density of a country's online fundraising campaign and average donations per campaign day in that country.

H4c: The higher the prosocial cultural norms, the stronger the association between the network centralization of a country's online fundraising campaign and average donations per campaign day in that country.

METHODS

The Movember campaign

The context of our research is the 2013 Movember fundraising campaign. The Movember Foundation is a global charity organization that aims to help men live happier, healthier, and longer lives. Since 2003, Movember has mobilized 5.2 million fundraisers, involving both men and women, to raise a total of 710 million US dollars in funding for health projects related to prostate cancer, testicular cancer, and mental health. Fundraisers raise awareness and funds by, for example, growing their moustaches during the month November and asking their social networks – including family, friends, and colleagues – to donate to Movember. Fundraisers may join the campaign individually or as part of a team. Each year, the campaign begins at the end of October with the recruitment of fundraisers. Male fundraisers (91% of the fundraisers in 2013) may shave off their moustache shortly before the campaign begins on the 1st of November and are asked to post regular pictures of their facial hair. The campaign concludes at the end of November. Fundraisers use both digital media (mainly Twitter, Facebook, and Instagram) and offline events to raise donations.

We obtained data about the Movember campaign for the 24 countries with the largest number of Movember fundraisers: Australia, Belgium, Brazil, the Czech Republic, Denmark, Finland, France, Germany, the autonomous territory of Hong Kong, Ireland, Italy, Japan, Mexico, the Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The distribution of the total sum of donations (funds raised) during the 2013 Movember campaign in all 24 countries is presented in Figure 1.

<Figure 1, about here>

Data and Measurements

Our dependent variable $DONATIONS_{ct}$ is based on Google Analytics financial data obtained from the Movember campaign organization. It measures – for each day between October 15 and December 15 2013 – the average amount of money donated to the Movember campaign by visitors who entered the Movember website via a link in a Twitter message. The donations were made through a digital payment system and directly transferred to Movember's bank account. Donations are log-transformed[2] and measured in AUS$ per campaign day, per country. The log-transformed variable $DONATIONS_{ct}$ ranges between 0 and 4.90.

Network structure is measured using three variables that vary over time and across countries: $NETWORK\ SIZE_{ct}$, $NETWORK\ DENSITY_{ct}$ and $NETWORK\ IN\text{-}DEGREE\ CENTRALIZATION_{ct}$, all of which are measured per campaign day per country using Twitter data. These data were collected between October 15 and December 15, 2013. We collected 1,016,205 Tweets from Twitter's archive that contain the hashtag #Movember. Collaboration with Twitter resulted in the collection of *all* public Tweets containing the Movember hashtag, which is a more complete sample than those collected using APIs that may have sample biases or representation issues (Gonzalez-Bailon, Wang, Rivero, Borge-Holthoefer, & Moreno, 2014). The Twitter data, however, do not contain any information on the country of the Twitter user.[3] Hence, we developed and used a Naïve Bayes model to determine the country of the tweet's user. The country classifier has a weighted accuracy of 94% for the countries under study (Reference removed for anonymity).

After splitting the dataset with the country classifier into 24 countries, we used the Twitter Capture and Analysis Toolset (TCAT) tool of the University of Amsterdam's Digital Methods Initiative (Borra & Rieder, 2014) to develop a social graph of mentions for each campaign day in each country.

[2] We added a small constant (*c*=1) to the to-be-transformed variables to avoid the logarithm of 0, e.g., an average of AUS$ 0 funds raised in one day.

[3] Approximately 2-4 percent of all Tweets contain geolocations (latitude and longitude). We used these Tweets as a reference dataset when developing the classifier.

This social graph represents a communication network of the Movember campaign with interactions about Movember as tie type (Borgatti, Everett & Johnson, 2018; Gonzalez-Bailon & Wang, 2016). In this bidirectional graph, Twitter users are represented by nodes. An edge between nodes is made for each Tweet in which a user mentions (@user) another user. Hence, our network includes mentions, replies and retweets sent by a user. We did not remove Twitter users from the network, so Twitter accounts related to the Movember organization are part of the dataset. We used NodeXL software to calculate the whole network metrics for each day in each country.

NETWORK SIZE$_{ct}$ is measured by the log of the number of unique Twitter users in a country on each campaign day who send a Twitter message containing the word ‘Movember’; it ranges between 0 and 10.99. *NETWORK DENSITY*$_{ct}$ is measured by the ratio of the number of actual times that a Twitter user is mentioned by another Twitter user on a campaign day to the number of possible mentions in the respective network (Jin, Girvan, & Newman, 2001). This variable ranges between 0.00002 and 0.66667 and is measured for each campaign day in all countries. *NETWORK IN-DEGREE CENTRALIZATION*$_{ct}$ assesses how central the most central Twitter user in a country is in relation to how central all the other Twitter users in that country are (Jin et al., 2001). In-degree centralization is measured by the ratio of the sum of differences in in-degree centrality between the most central Twitter users in a country and all other Twitter users in that country to the theoretically largest sum of differences in any network of the same size. This variable ranges between 0.01 and 1 and is also measured for each campaign day in all countries.

We measure the variable *PROSOCIAL CULTURAL NORMS*$_{c}$ using data from the World Giving Index 2011 (CAF, 2012). This variable is calculated by averaging the percentage of people who volunteered their time in a country and the percentage of people who had helped a stranger three months prior to the survey in 2011. To avoid problems regarding endogeneity, we did not include the percentage of people in a country who donated money to a prosocial goal measured in the World Giving Index (only moderately correlated with the other two items, Volunteering and Helping a stranger), and we used data from the 2011 edition rather than the 2013 edition to avoid simultaneity. Furthermore, to examine endogeneity issues, we conducted a Hausman specification test, which was negative (p = 0.2268) (Hausman, 1978). We therefore estimated random effect models. Last, the sample of the Movember campaign population strongly deviates from the representative sample of the World Giving Index. The variable varies across countries but not over campaign days, and it ranges between 22 and 58.

In the analysis, we control for GDP_c, which is the gross domestic product per capita in AUS dollars per country in 2010, as we expect countries' differences in standards of living to explain the variance in the average donation amount[4]. The variable GDP_c is obtained from the Penn World Table and ranges between AUS$ 9,014 and AUS$ 60,331.

Table 1 presents the means, standard deviations, and ranges of the dependent variable and independent variables. Table 2 presents the bivariate correlations between the variables in our analysis.

<Table 1, about here>

<Table 2, about here>

RESULTS

To test our hypotheses, we analyze a random effect Tobit model with Gauss-Hermite quadrature that includes campaign days (level 1, N=62) nested within countries (level 2, N=24). The non-negative values of the dependent variable (i.e., there are no negative donations possible) justify a Tobit model left-censored at 0 (see, e.g., Reece, 1979; Lankford & Wyckoff, 1991), which provides more accurate estimates. The total number of observations is 1,488 for all models. Apart from campaign day (*TIME)*, we included the polynomial term, *TIME x TIME,* in the model to account for non-linear curving of our

[4] We considered internet penetration rate as a country-varying control variable, because the number of internet users in a country may influence the network size, density and centralization of an online health campaign. However, this control variable was not significant in the null model and also highly correlated with the GDP per capita control variable. This make sense, because internet penetration is a similar indicator of a country's living standards. We would risk multicollinearity and subsequent overfitting our models with including them both. Hence, we decided not to include internet penetration as a control variable.

model (Rabe-Hesketh & Skrondal, 2012). The model-parameters were estimated using Stata/IC 14. Table 3 presents the results for seven different models. In model 1, we estimate our null model, including only a constant and random variation between and within countries, with GDP_c as the control variable. The average score for the *DONATIONS* variable is AUS$ 322.31 ($10^{2.51}$); this varies significantly among countries and among campaign days, representing 38% (100*(1.91/(1.91+3.12))) and 62%, respectively, of the total variance in donations.

<Table 3, about here>

Model 2 estimates the relationship of network structure (time-varying) with average donation amount (time-varying). We find a positive relationship of network size (p=.000) and a negative relationship of network in-degree centralization (p=.008) with average donation amount. There is, however, no significant relationship (p=.199) between network density and average donation amount. This finding suggests that larger and more decentralized campaign networks result in higher average donation amounts, thus confirming hypotheses 1 and 3. However, hypothesis 2 on density is rejected. Model 3 adds prosocial cultural norms (country-varying) to the null model. The regression results reveal a positive and significant relationship of countries' prosocial cultural norms with average donation amount when controlling for GDP_c. We expected that countries with higher levels of prosocial cultural norms would have more donations. The coefficient of the prosocial cultural norms variable is positive, in the expected direction, and significantly different from zero (p=0.000). This implies, at least provisionally, that hypothesis 4 is confirmed. Model 4 simultaneously estimates the relationship between prosocial cultural norms and network structure and reveals similar results to those observed in models 2 and 3.

In models 5-7, we add the interaction terms to model 4. Hypothesis 4a states that the relationship of network size with the average donation amount in a campaign is stronger in countries with higher prosocial cultural norms. The results of model 5, however, reject this hypothesized relationship (*p*=0.213). Hypothesis 4b states that the relationship of network density with the average donation amount in a campaign is stronger in countries with higher prosocial cultural norms. In model 6, however, we find a negative and significant interaction effect (*p*=0.025). This implies that the relationship of network density with the average donation amount is *weaker* in countries with higher levels of prosocial cultural norms. Last, the results of model 7 reveal no significant (*p*=0.681) interaction effect between prosocial cultural norms in a country and network in-degree centralization. Hence, we reject hypothesis 4c and conclude that prosocial norms are not related to the relationship between network centralization and the average donation amount.

Together, the variables in model 6 explain 34% (100 * (1-1.27/1.91)) of the variance in donations among countries and 2% (100*(1-3.07/3.12)) of the variance among campaign days compared to the initial null model (model 1). To check for outliers among countries, we conducted a robustness test by estimating 24 full models, each excluding a specific country from the analysis. The significance of in-degree network centralization became weaker in three models (Brazil, France and Mexico) but remained below a 10% significance level. All other relationships remained the same in the models.

CONCLUSION

In this paper, we studied to what extent and how a country's prosocial cultural norms modify the relationship between an online campaign's network structure and the average donation amounts collected in 24 countries during 62 campaign days.

The multilevel analysis of Movember's Twitter campaign suggests that the campaign network's size and decentralization, as well as prosocial cultural norms, are positively related to average donation amount. The positive relationship between network size and donation behavior is consistent with the logic of connective action: digital media enable large groups to engage in collective action (Bennett & Segerberg, 2012), diminishing the free-riding problem of conventional collective action. Overall, our analysis suggests that large, decentralized campaign networks, characterized by clusters of network members rather than few central network members, are most effective in collecting donations. The results for the interaction effects between the network structure of the online campaign and the country's prosocial cultural norms are mixed. Our results indicate that the higher the prosocial cultural norms in a country, the *weaker* the relationship between the density of the social network of a country's online health campaign and average campaign donations. A possible explanation for this unexpected finding is that the threshold for donation behavior is lower in countries with higher prosocial cultural norms, which may decrease the importance of social influence from a campaign network or cause people to feel over-solicited as the number of solicitations increases with the density of the network (Bekkers & Wiepking, 2011). Consequently, fundraisers in dense networks may have overlapping social networks of potential donors, possibly decreasing the average donation raised because potential donors are over-solicited. A rival explanation is that in countries with high prosocial cultural norms, there is less need for strong network structures to engage people in (collective) prosocial behavior. Last, prosocial cultural norms do not significantly interact with network centralization, which implies that higher levels of prosocial cultural norms do not increase or decrease the association of networks containing central actors, such as a strong campaign organization or celebrities, with donation behavior.

Our study contributes to previous research on the role of networks and cultural norms in (collective) prosocial behavior in three ways. First, we extend the study of (collective) prosocial behavior to the interaction between the structure of social networks and descriptive prosocial cultural norms, expanding on earlier studies that have analyzed the effects of cultural norms and networks – separately – on (collective) prosocial behavior (Bekkers & Wiepking, 2011; Ruiter & De Graaf, 2006). Our analysis does not conclude that higher levels of prosocial cultural norms are required for people to live up to the pressure from all sources of network closure that campaigns may provide. Instead, higher levels of prosocial cultural norms decrease the positive relationship of network density with average donation amount. Second, we examine whether the use of digital media changes the premise of resource mobilization theory, which suggests that large-scale collective action requires network closure (Bennett & Segerberg, 2012; Saxton & Wang, 2014). Specifically, we highlight the relationship between online mobilization structures and charitable giving. Finally, we use historical Twitter data to track the process and outcome of large-scale fundraising campaigns over time (van Leeuwen & Wiepking, 2013).

In this study, we used a communication network based on interactions between Twitter users to operationalize the network structure. We recognize that this operationalization differs from traditional operationalizations of social capital that were based on offline, civic participation (Putnam, 2000) and long-lasting relationships (Bourdieu, 1985). Most scholars agree that social capital is derived from the social structure among actors and their ties, and that this social structure may help actors to achieve their individual and collective social goals (Portes, 1998; Lee & Lee, 2010). Hence, communication interactions between actors typically embody such social structure nowadays (Rojas et al., 2011; Ashcraft et al., 2009; Putnam & Nicotera, 2008). Still, we should be aware of how different operationalizations of social capital may influence the results. For example, Cox et al. (2018) investigated the effect of online and offline social capital on observed prosocial behavior. They find that both online and offline operationalizations of social capital positively influence donations raised. A difference is that online social capital had a stronger effect on online donations raised, while offline social capital had a stronger effect on offline donations raised. Future research may test our results with different operationalizatoins of social capital (e.g. attendance of fundraising events).

By creating a complete dataset (with the exception of private Tweets) in collaboration with the social media organization Twitter, we were able to minimize the biases that may result from smaller samples (Gonzalez-Bailon et al., 2014). However, the generalizability of our study is limited to the Twitter population that was used to measure the network structure variables (Lewis et al., 2015; Lewis, Kaufman, Gonzalez, Wimmer, & Christakis, 2008). The Movember campaign uses additional media channels to raise funds, such as Facebook, offline events and e-mail. Despite the similarity between online and offline networks (Dunbar, Arnaboldi, Conti, & Passarella, 2015), we may expect the Twitter population to be especially active, young and politically engaged. Furthermore, a large majority of the population is male due to the nature of the campaign. Hence, the conclusions of our research are limited to health campaigns on Twitter, particularly in the context of the Movember campaign. Despite the limitations of the sample, we aimed for an accurate estimation of the relations by measuring only the donations that were received from Internet users who entered Movember's website via Twitter. Furthermore, our study focused on entire networks based on mentions on Twitter. To better grasp the dynamics and outcomes of important fundraisers (e.g., celebrities or campaigners), future research could study the centrality of fundraisers over time. Third, our analysis focuses on the campaign network and hence does not include the influence of external stakeholders or other information sources beyond social media that may influence charitable giving, such as mass media (Brown & Minty, 2008; Lobb, Mock & Hutchinson, 2012) and government funding (De Wit, Bekkers & Van Groenou, 2017). Recently, Li and McDougle (2017) pointed to the mix of information sources that donors use to make decisions about their charitable giving. Future research may expand our analysis by using such a mix of information sources. Last, our study measured prosocial cultural norms on a macro level with international survey data (the World Giving Index). On a macro level, future research could use religiosity as a source of prosocial norms in online campaigns (e.g., Ruiter & De Graaf, 2006). On a micro level, future research could use automated content analysis to measure the prosocial norms of individual campaign members, such as their perceptions of injustice and identity (Reference removed for anonymity).

Practically, our study provides strategies that online campaigners in nonprofit organizations, government agencies and firms can use to develop online fundraising campaigns that make better use of social network structures and existing prosocial norms. Overall, our study shows that digital campaigners would benefit most by focusing their efforts on increasing the number of fundraisers (even those who are peripheral in a network) and, especially in countries with low levels of prosocial cultural norms, on creating dense sub-clusters of campaign members who participate via an organization, college, association, etc. Exploring the role of (social) identity in the relation between network structure and (collective) prosocial behavior may be an interesting research avenue that has the potential to improve our understanding of the interplay between structural factors and collective action.

TABLES AND FIGURES

Table 1: Descriptive statistics (n countries=24, n campaign days=62)

		Independent variables				**Dependent variable**	**Control variable**
Countries	**n**	**Prosocial norms (WGI aggregated scale)**	**Network size**[5]	**Network density**	**Network centralization**	**Average donation amount (AUS$)**[5]	**GDP/capita (AUS$ 1000) in 2010**
Range	62	22-58	6.65-9005.25	0.000-0.231	0.063-0.462	0.01-34.42	9.01-60.33
			Mean (SD)	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	
Australia	62	52	393.26 (380.97)	0.007 (0.009)	0.139 (0.098)	32.98 (38.97)	50.32
Belgium	62	32	58.73 (57.32)	0.046 (0.076)	0.143 (0.194)	5.25 (11.98)	40.24
Brazil	62	31	157.95 (414.72)	0.028 (0.052)	0.309 (0.306)	2.75 (17.51)	9.87
Czech Republic	62	27	22.55 (27.83)	0.124 (0.156)	0.279 (0.303)	10.75 (27.40)	25.79
Denmark	62	36.5	42.34 (43.60)	0.047 (0.071)	0.140 (0.173)	12.45 (49.34)	39.21
Finland	62	41	83.27 (103.97)	0.048 (0.091)	0.157 (0.216)	6.28 (9.65)	36.81
France	62	32.5	220.32 (214.66)	0.011 (0.012)	0.152 (0.141)	11.28 (23.67)	35.65
Germany	62	40.5	89.58 (98.78)	0.029 (0.042)	0.152 (0.195)	7.13 (13.28)	38.75
Hong Kong	62	37.5	20.31 (20.45)	0.104 (0.130)	0.267 (0.286)	36.15 (120.91)	42.43
Ireland	62	51.5	244.03 (228.34)	0.011 (0.014)	0.090 (0.093)	19.00 (29.01)	38.62
Italy	62	23	69.18 (97.36)	0.045 (0.089)	0.207 (0.236)	1.57 (5.98)	32.16
Japan	62	27	28.29 (29.14)	0.088 (0.126)	0.229 (0.278)	2.18 (9.77)	35.07
Mexico	62	37	60.87 (90.12)	0.05 (0.09)	0.230 (0.242)	1.70 (12.70)	13.59
Netherlands	62	44	289.95 (336.91)	0.009 (0.011)	0.096 (0.076)	12.42 (14.10)	43.06
New Zealand	62	54	63.52 (60.32)	0.040 (0.052)	0.151 (0.181)	8.31 (20.31)	32.35
Norway	62	41.5	47.53 (52.46)	0.068 (0.112)	0.177 (0.222)	114.36 (257.63)	59.66
Portugal	62	22	6.65 (15.97)	0.231 (0.191)	0.462 (0.413)	0.17 (0.92)	22.85

[5] These are absolute instead of log-transformed values to support interpretation of the descriptive statistics.

Singapore	62	22	42.08 (50.98)	0.097 (0.155)	0.263 (0.320)	4.64 (15.87)	60.33
South Africa	62	44.5	254.44 (427.28)	0.017 (0.037)	0.063 (0.051)	49.95 (133.96)	9.01
Spain	62	33.5	243.97 (207.76)	0.010 (0.010)	0.123 (0.095)	0.97 (0.93)	31.19
Sweden	62	31.5	65.71 (68.58)	0.064 (0.120)	0.195 (0.245)	42.85 (99.17)	41.38
Switzerland	62	38.5	17.89 (18.52)	0.100 (0.112)	0.199 (0.244)	87.13 (200.65)	45.91
UK	62	45.5	9,005.21 (9,416.36)	0.000 (0.001)	0.111 (0.127)	17.06 (7.98)	38.92
USA	62	58	4,862.79 (5,461.48)	0.001 (0.001)	0.126 (0.114)	52.93 (62.35)	47.12

Table 2: Bivariate correlations

	Variables	1	2	3	4	5	6	7	8
1	Average donation amount (log)	1							
2	Network size (log)	0.49***	1						
3	Network density	-0.23***	-0.53***	1					
4	Network in-degree centralization	-0.18***	-0.26***	0.68***	1				
5	Prosocial cultural norms	0.37***	0.48***	-0.25***	-0.18***	1			
6	GDP	0.21***	0.08*	-0.00	-0.06*	0.28***	1		
7	Time	0.03	-0.09	0.05*	0.24***	0	0	1	
8	Time X Time	-0.04	-0.12***	0.15***	0.31***	0	0	0.97***	1

* = p<0.05, ** = p<0.01, *** < p<0.001

Table 3: Multilevel Tobit regression coefficients explaining donations to the 2013 Movember campaign (n countries=24, n campaign days=62)

	Model I: Null model		**Model II: Structure**		**Model III: Norms**		**Model IV: Structure and Norms**	
	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*
Intercept	-10.56 (.76)	.000***	-10.39 (.93)	.000***	-13.82 (.99)	.000***	-12.63 (1.36)	.000***
Country-campaign day variables								
Network size (log)			1.01 (.09)	.000***			.91 (.12)	.000***
Network density			3.01 (2.34)	.199			2.70 (2.40)	.261
Network in-degree centralization			-2.16 (.82)	.008**			-1.90 (.83)	.021*
Time	.41 (.03)	.000***	.19 (.03)	.000***	.40 (.03)	.000***	.21 (.04)	.000***
Time X Time	-.01 (.00)	.000***	-.00 (.00)	.000***	-.01 (.00)	.000***	-.00 (.00)	.000***
Country variables								
Prosocial cultural norms					.15 (.02)	.000***	.07 (.03)	.005**
GDP/capita (AUS $1000)	.10 (.01)	.000***	.07 (.02)	.000***	.04 (.01)	.010*	.06 (0.02)	.006**
Interactions								
Network size (log) X Norms								
Network density X Norms								
Network in-degree centralization X Norms								
Variance component								
Country-campaign day variance	3.12 (.11)		3.08 (.11)		3.12 (.11)		3.08 (.11)	
Country variance	1.91 (.14)		1.26 (.18)		1.48 (.15)		1.24 (.49)	
Observations	1,488 (of which 987 left-censored observations)		1,488 (of which 987 left-censored observations)		1,488 (of which 987 left-censored observations)		1,488 (of which 987 left-censored observations)	

Note: The dependent variable is average donation amount (log), with a lower censoring level of 0. † = p<0.1, * = p<0.05, ** = p<0.01, *** = p<0.001

	Model V: Size X Norms		**Model VI: Density X Norms**		**Model VII: Centralization X Norms**	
	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*
Intercept	-15.44 (2.25)	.000***	-12.72 (1.20)	.000***	-12.49 (1.38)	.000***
Country-campaign day variables						
Network size (log)	1.41 (.42)	.001**	.86 (.10)	.000***	.91 (.12)	.000***
Network density	3.80 (2.54)	.134	19.10 (7.38)	.010*	2.96 (2.48)	.233
Network in-degree centralization	-2.02 (.83)	.015*	-1.98 (.83)	.017*	-2.96 (2.72)	.275
Time	.22 (.04)	.000***	.21 (.03)	.000***	.21 (.04)	.000***
Time X Time	-.00 (.00)	.000***	-.00 (.00)	.000***	-.00 (.00)	.000***
Country variables						
Prosocial cultural norms	.014 (.05)	.010*	.08 (.02)	.000***	.07 (.03)	.013*
GDP/capita (AUS $1000)	.06 (.02)	.005**	.00 (.00)	.003**	.06 (.02)	.005**
Interactions						
Network size (log) X Norms	-.01 (.01)	.213				
Network density X Norms			-.54 (.24)	.025*		
Network in-degree centralization X Norms					.02 (.07)	.681
Variance component						
Country-campaign day variance	3.08 (.11)		3.07 (.11)		3.08 (.11)	
Country variance	1.11 (.20)		1.27 (.27)		1.25 (.50)	
Observations	1,488 (of which 987 left-censored observations)		1,488 (of which 987 left-censored observations)		1,488 (of which 987 left-censored observations)	

Note: The dependent variable is average donation amount (log). † = p<0.1, * = p<0.05, ** = p<0.01, *** = p<0.001

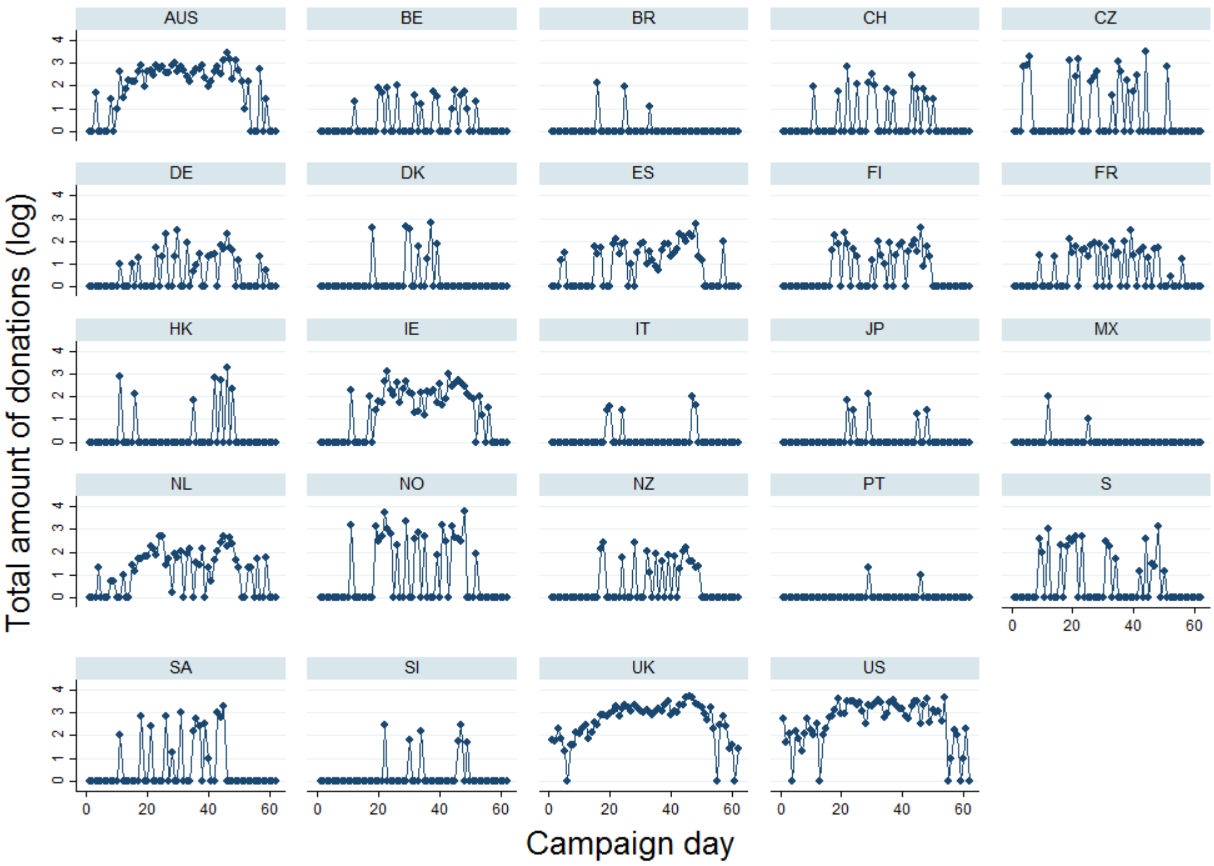

Figure 1: The distribution of donations during the 2013 Movember campaign in 24 countries.

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