The Influence of Prosocial Norms and Online Network Structure on Prosocial Behavior: An Analysis of Movember's Twitter Campaign in 24 Countries

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Abstract: Sociological research points at norms and social networks as antecedents of prosocial behavior. To date, the literature remains undecided on how these factors jointly influence prosocial behavior. Furthermore, the use of social media by campaign organizations may change the need for formal networks to organize large-scale collective action. Hence, in this paper we examine the interplay of prosocial norms and the structure of *online* social networks on *offline* prosocial behavior. For this purpose we use donation data from the global Movember campaign, messages about the Movember campaign on the online social networking site Twitter, and data from the World Giving Index. A multi-level analysis of Movember's campaigns in 24 countries finds support for the logic of connective action: larger and more decentralized networks raise more donations. Furthermore, we find that the effect of prosocial norms on donations is decreased by larger and denser campaign networks

INTRODUCTION

"Why do people engage in behavior that benefits one or more others?" is one of the fundamental questions in sociology. So far, research discusses two key factors that explain why individuals engage in prosocial behavior: *norms* and *networks* (Bekkers and Schuyt 2008, Bekkers and Wiepking 2010, Simpson and Willer 2015). To date, however, most studies examine the influence of either norms or networks on prosocial behavior (Bekkers and Wiepking 2010, Ruiter and De Graaf 2006, Simpson and Willer 2015). People with a prosocial motivation may require the pressure from their social network to live up their intentions (De Graaf, Need and Ultee 2004). Hence, our study follows calls (Bekkers and Wiepking 2010) for research on the interaction between prosocial norms and social network structure to provide a multi-level explanation of prosocial behavior.

Social media is increasingly used by fundraising organizations to promote prosocial behavior, e.g. acquiring funding for health research (Chou et al. 2013, Maher et al. 2014, Wehner et al. 2014). However, little is known about how prosocial norms and *online* social networks jointly stimulate *offline* prosocial behavior (Saxton and Wang 2013, van Leeuwen and Wiepking 2013). An emerging body of sociological research argues that the low costs, speed, scale and connectivity of digital media may reduce the need for formal, centralized organization of collective action (Bennett and Segerberg 2012, Bimber, Flanagin and Stohl 2005, Lupia and Sin 2003, Saxton and Wang 2013). Hence, the use of social media may change the effect of social network structure on prosocial behavior.

Following both theoretical gaps, the research question of our study is: "In what way do (a) prosocial norms and the online social network structure and (b) their interplay influence the cumulative amount of donations collected in a Twitter fundraising campaign?" The empirical setting is the global Movember campaign. In 2013, Movember participants raised approximately 147 million dollar for men-related cancer and mental health research. We use longitudinal data from the Movember's Twitter campaign in 24 countries to study how the online network structure of the campaign reinforces the effect of prosocial norms.

THEORY AND HYPOTHESES

Prosocial norms

Individuals donate to a campaign organization when they are *convinced* of the cause of the campaign (Andreoni 2006), i.e. they have prosocial motivations. In general, literature shows that individuals who have strong prosocial motivations are more likely to donate to a cause (Bekkers and Schuyt 2008, Farmer and Fedor 2001). Prosocial motivations are embedded in the prosocial norms of a culture. Researchers point out that *descriptive norms*, i.e., "what most people do", influence people to behave similarly (Cialdini, Reno and Kallgren 1990) and hence *prosocial norms* foster the adoption of prosocial behavior. Hence, we propose:

H1: The higher the level of prosocial norms in a country, the higher the donations in online campaigns in that country.

Network structure

The structure of social networks is considered as essential to the organization of collective action, such as donating or protesting (González-Bailón et al. 2011, Gould 1993, Marwell, Oliver and Prahl 1988). Network closure, which represents how strongly interconnected nodes are, is considered as a driver of collective action (Marwell, Oliver and Prahl 1988) and subsequent prosocial behavior (Bekkers et al. 2008, Brown and Ferris 2007). However, empirical research of indicators of network closure, such as membership of voluntary organizations, does not show a strong relation with volunteering and donation behavior (Bekkers and Veldhuizen 2008, Brown and Ferris 2007). A more detailed analysis of the elements of network closure (size, density and centralization) may explain under what conditions network closure leads to donations behavior (Burt 2001).

Network size represents the number of nodes in a social network, i.e. the participants in the campaign. The amount of donations may be lower in larger campaign networks due to "free rider-effects" (Olson and Caddell 1994). In large groups, unmotivated participants tend to refrain from a substantial contribution, while still benefiting from the common goal. Hence, large campaign networks may provide less social pressure on participants to give a substantial donation (Bekkers and Wiepking, 2010). However, network size also stimulates collective action. Large networks may activate more donors who are solicited by other network members, as more individuals are (indirectly) connected (Bekkers and Wiepking 2010, Saxton and Wang 2013). Moreover, the low costs and high speed of social media may decrease the free-rider problem, as participants can donate small amounts of money without a lot of transaction costs (Bennett and Segerberg 2012, Bimber, Flanagin and Stohl 2005, Lupia and Sin 2003). Therefore, we propose:

H2: The higher the number of nodes in a country's online health campaigns' social network, the higher the campaign donations 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 are important for collective action (Gould 1993, Marwell, Oliver and Prahl 1988) because they play a key role in the recruitment and mobilization processes (Tilly 1978). Consequently, network density may stimulate the diffusion of social information and lead to social influence mechanisms. Indeed, it has been found that donations are rather strongly related to social pressure from a network (Bekkers and Schuyt 2008, Bekkers and Wiepking 2010). Hence, we propose:

H3: The higher the density of a country's online health campaigns' social network, the higher the campaign donations 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 to which most participants have ties (Diani 1997). Network centralization is a source of network closure as central actors connect most participants within the network. Several scholars support that network centralization stimulates collective action (Marwell, Oliver and Prahl 1988). A highly centralized campaign network can provide incentives to participants and central actors to coordinate collective action and prevent free-riding behavior (Ganley and Lampe 2009, Marwell, Oliver and Prahl 1988). However, scholars increasingly argue that the use of digital media for the organization of collective action diminishes the importance of network centralization (Bennett and Segerberg 2012, Bimber, Flanagin and Stohl 2005, Castells 2002, Lupia and Sin 2003). Their central claim is that digital media decrease the marginal costs for organizers and participants in collective action. In this way, they enable so-termed *connective action* for large numbers of people, without a centralized mobilizing structure (Bennett and Segerberg 2012).. Following these different positions, we test two competing hypotheses:

H4a: The higher the centralization of a country's online health campaigns' social network, the higher the campaign donations in that country.

H4b: The higher the centralization of a country's online health campaigns' social network, the lower the campaign donations in that country.

Prosocial norms and network structure

Donation behavior is the outcome of an aspiration to behave prosocially and the opportunity to act in accordance with this wish (De Graaf, Need and Ultee 2004). Being part of a social network provides individuals with constraints or opportunities to live up to a prosocial norm. Resource mobilization theory indeed imply that individuals require mobilizing structures, such as campaigns or religious membership, to transform individual motivations into collective action (McCarthy and Zald 2001). Hence, we propose that the sources of network closure (size, density and centralization) reinforce the effect of pro-social norms on donations:

H2a: The effect of prosocial norms is stronger in countries where online health campaigns have larger social networks.

H3a: The effect of prosocial norms is stronger in countries where online health campaigns have denser social networks.

H4c: The effect of prosocial norms is stronger in countries where online health campaigns have more centralized social networks.

Figure 1 presents the conceptual model and the hypotheses.

<Figure 1, about here>

DATA AND OPERATIONALIZATION

Our dependent variable $DONATIONS_{ct}$ is based on Google analytics data obtained from Movember. It measures – for each day between October 15 and December 15 2013 – the cumulative amount of donations to the Movember campaign from visitors who entered the Movember website via a link in a Twitter message. Donations are log-transformed and measured in US Dollars per campaign day, per country. The variable donations ranges between 0 and 79,568.

We measure the variable *PROSOCIAL NORMS*$_c$ using data from the World Giving Index 2013 (CAF 2014). It is measured as the average of the percentage of people in a country who donate money to charity, volunteer their time, and helped a stranger in 2013. The variable varies between countries but not over time and ranges between 0 and 100.

Network structure is measured with three variables: *NETWORK SIZE*$_{ct}$, *NETWORK DENSITY*$_{ct}$ and *NETWORK IN-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 in this period that contain the hashtag #Movember. A Naïve Bayes model determined the country of the tweet's user with a weighted accuracy of 94% for the countries under study (Reference removed for anonymity). *NETWORK SIZE*$_{ct}$ is measured by the log of the number of unique Twitter users in a country on each campaign day. It ranges between 0 and 59,292 nodes. *NETWORK DENSITY*$_{ct}$ is measured by the ratio of the number of actual times that a Twitter user is mentioned by another Twitter user to the number of possible mentions in a network (Jin, Girvan and Newman 2001). This variable ranges between 0.00002 and 0.66667. *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, Girvan and Newman 2001). It is measured by the ratio of the sum in 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 such sum of differences in any network of the same size. This variable ranges between 0.01 and 1.

In the analyses, we control for *GDP*$_c$, which is the Gross Domestic Product per capita in US dollars per country, in 2010. The variable *GDP*$_c$ is obtained from the Penn World Table and ranges between $8,907 and $59,615.

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

<Table 1, about here>

<Table 2, about here>

RESULTS

The growth curves of cumulative amount of donations during the 2013 Movember campaign in all countries is shown in figure 2.

<Figure 2, about here>

To test our hypotheses, we analyze the dataset as a hierarchical structure of campaign-days nested within countries. The model-parameters were estimated using Stata/IC 13.1. Table 3 presents the results for five different models. In model 1, we estimate only a constant and random variation between- and within countries. The average score on the DONATION variable is \$322,31 ($10^{2.51}$); this varies significantly between countries and between campaign days: respectively 41.8% (100*(0.81/0.81+1.13)) and 58.2% of the total variance in donations.

<Table 3, about here>

Model 2 shows a positive and significant effect of prosocial norms of countries on the cumulative amount of donations, controlled for GDP. We expected that countries with higher levels of prosocial norms will have more donations. The coefficient of the prosocial norms variable is positive, in the expected direction, and statistically different from zero (p=.011). This means, at least provisionally, that hypothesis 1 is confirmed. Model 3 examines the effect of network structure on donations. We find a positive and significant effect of both network size and network density. There is no significant effect of network centralization. This means that hypotheses 2 and 3 are, for now, confirmed. Hypothesis 4a and hypothesis 4b are both rejected. Model 4 simultaneously estimates the effects of prosocial norms and network structure with similar results as model 2 and 3. In model 5 we add the interaction terms to model 4. Hypothesis 2a expected that the effect of prosocial norms is stronger in countries where online health campaigns have larger social networks. The results of model 5 shows a reversed effect: a larger network size seems to reduce the effect of prosocial norms (p=0.04). Hypothesis 3a expected the effect of prosocial norms to be stronger in countries where online health campaigns have denser social networks. Similar to hypothesis 2a, we find a negative and significant interaction effect (p=0.00). This implies that the effect of prosocial norms is weaker in countries where online health campaigns have denser social networks. Finally, based on model 5, we can confirm (p=0.01) hypothesis 4c, which states that the effect of prosocial norms is stronger in countries where online health campaigns have more centralized social networks. Together, the variables in our model explain 17% (1-0.68/0.82) of the variance in donations between countries and 4.2% (1-0.45/0.47) of the variance between campaign days.

DISCUSSION AND CONCLUSION

In this paper we studied in what way (a) national prosocial norms, b) the online social network structure of fundraising campaigns on Twitter, and (c) the interplay between norms and network structure influence the cumulative amount of donations collected in 24 countries. Table 4 provides an overview of the hypotheses and the results.

<Table 4, about here>

The multi-level analysis of Movember's Twitter campaign confirms that prosocial norms and the size and density of a Twitter campaign positively affect the amount of donations. The link between network size and donation behavior is in line with the logic of connective action: digital media enable large groups to engage in collective action (Bennett and Segerberg 2012). Furthermore, we have no conclusive evidence that decentralized or centralized networks drive prosocial behavior. The results on the interaction between prosocial norms and the network structure of the online campaign were more complex than expected. Network size and density decrease instead of increase the effect of prosocial norms on donation behavior, so people in countries with high levels of prosocial norms seem to be discouraged by large and dense online campaign networks. A possible explanation is that the threshold for donation behavior is lower in countries with higher prosocial norms, which decreases the importance of social influence from the campaign network, or people feel over solicited on the cause as the number of solicitations increase with the size and density of the network (Bekkers and Wiepking 2010). Network centralization does interact with prosocial norms, which implies that networks with central actors, such as a strong campaign organization or the presence of celebrities, have a stronger effect in countries with higher levels of prosocial norms.

Our study contributes to previous work in three ways. First, we expand the study of non-religious prosocial behavior to the interaction between descriptive prosocial norms and the structure of social networks, expanding earlier studies on separate effects of norms and networks on prosocial behavior (Bekkers and Wiepking 2010, Ruiter and De Graaf 2006). Second, we examine how the use of digital media changes the premises of resource mobilization theory that large-scale collective action needs network closure (Bennett and Segerberg 2012, Saxton and Wang 2013). Last, we use historical Twitter data to track the process and outcome of large-scale fundraising campaigns over time (van Leeuwen and Wiepking 2013).

Practically, our study provides guidelines to online campaigners at non-profit organizations, government agencies and firms how to develop online advocacy campaigns that better transform latent prosocial norms into donations.

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

		Independent variables				Dependent variable	Control variable
Countries	**n**	**PROSOCIAL NORMS**	**NETWORK SIZE**	**NETWORK DENSITY**	**NETWORK CENTRALIZATION DEGREE**	**DONATIONS (per $1000)**	**GDP (US$1000) per capita in 2010**
Range	62	23-61	6.65-9005.25	0.000-0.231	0.063-0.462	0.01-34.42	8.91-59.62
			Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
Australia	62	55	393.26 (380.97)	0.007 (0.009)	0.139 (0.098)	9.28 (7.89)	49.73
Belgium	62	33	58.73 (57.32)	0.046 (0.076)	0.143 (0.194)	0.31 (0.24)	39.76
Brazil	62	26	157.95 (414.72)	0.028 (0.052)	0.309 (0.306)	0.15 (0.09)	9.75
Czech	62	23	22.55 (27.83)	0.124 (0.156)	0.279 (0.303)	7.20 (3.90)	25.49
Denmark	62	43	42.34 (43.60)	0.047 (0.071)	0.140 (0.173)	0.97(0.81)	38.75
Finland	62	33	83.27 (103.97)	0.048 (0.091)	0.157 (0.216)	0.80 (0.65)	36.37
France	62	28	220.32 (214.66)	0.011 (0.012)	0.152 (0.141)	0.68 (0.56)	35.22
Germany	62	40	89.58 (98.78)	0.029 (0.042)	0.152 (0.195)	0.53 (0.48)	38.29
Hong Kong	62	44	20.31 (20.45)	0.104 (0.130)	0.267 (0.286)	1.67 (1.55)	41.93
Ireland	62	57	244.03 (228.34)	0.011 (0.014)	0.090 (0.093)	3.67 (3.13)	38.16
Italy	62	44	69.18 (97.36)	0.045 (0.089)	0.207 (0.236)	0.09 (0.08)	31.78
Japan	62	26	28.29 (29.14)	0.088 (0.126)	0.229 (0.278)	0.14 (0.11)	34.66
Mexico	62	28	60.87 (90.12)	0.05 (0.09)	0.230 (0.242)	0.08 (0.04)	13.43
Netherlands	62	54	289.95 (336.91)	0.009 (0.011)	0.096 (0.076)	1.86 (1.58)	42.55
New Zealand	62	58	63.52 (60.32)	0.040 (0.052)	0.151 (0.181)	0.72 (0.56)	31.97
Norway	62	48	47.53 (52.46)	0.068 (0.112)	0.177 (0.222)	11.45 (8.76)	58.96
Portugal	62	29	6.65 (15.97)	0.231 (0.191)	0.462 (0.413)	0.01 (0.01)	22.58
Singapore	62	32	42.08 (50.98)	0.097 (0.155)	0.263 (0.320)	0.37 (0.33)	59.62
South Africa	62	30	254.44 (427.28)	0.017 (0.037)	0.063 (0.051)	3.15 (2.94)	8.91
Spain	62	42	243.97 (207.76)	0.010 (0.010)	0.123 (0.095)	0.97 (0.93)	30.82
Sweden	62	39	65.71 (68.58)	0.064 (0.120)	0.195 (0.245)	3.20 (1.89)	40.89
Switzerland	62	47	17.89 (18.52)	0.100 (0.112)	0.199 (0.244)	1.06 (0.80)	45.37
United Kingdom	62	57	9,005.21 (9,416.36)	0.000 (0.001)	0.111 (0.127)	26.11 (23.8)	38.46
United States	62	61	4,862.79 (5,461.48)	0.001 (0.001)	0.126 (0.114)	34.42 (27.83)	46.57

Table 2: Bivariate correlations

	Variables	1	2	3	4	5	6	7	8
1	Cumulative amount of donations (log)	1							
2	Prosocial norms	0.33***	1						
3	Network size (log)	0.44***	0.45***	1					
4	Network density	-0.21***	-0.21***	-0.62***	1				
5	Network centralization	-0.05	-0.18***	-0.35***	0.68***	1			
6	Time	0.66***	0.00	-0.02	0.05	0.24***	1		
7	Time X Time	0.56***	0.00	-0.13***	0.15***	0.32***	0.97***	1	
8	GDP per capita	0.21***	0.51***	0.07**	-0.01	-0.07**	0.00	0.00	1

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

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

	Model 1: Null model		Model 2: Norms		Model 3: Structure		Model 4: Norms and Structure		Model 5: Norms X Structure	
	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*	b (s.e.)	*p*
Intercept	-0.13 (.17)	.432	-1.80 (.54)	.001**	-1.20 (.64)	.009**	-1.98 (.54)	.000***	-2.03 (.54)	.000***
Level-1 variables										
Network size (log)					.05 (.02)	.009**	.05 (.02)	.015*	.07 (.02)	.001**
Network density					.65 (.23)	.005**	.64 (.23)	.006**	3.80 (.70)	.000***
Network centralization					-.10 (.08)	.230	-.10 (.08)	.254	-.79 (.27)	.003**
Time	.15 (.00)	.000***	.15 (.00)	.000***	.15 (.00)	.000***	.15 (.00)	.000***	.14 (.00)	.000***
Time X Time	-.00 (.00)	.000***	-.00 (.00)	.000***	-.00 (.00)	.000***	-.00 (.00)	.000***	-.00 (.00)	.000***
Level-2 variables										
Prosocial norms			.04 (.14)	.011*			.03 (.01)	.020*	.03 (.01)	.021*
GDP/Capita ($US 1000)			.01 (.01)	.616	.02 (.01)	.055†	.01 (.01)	.527	.01 (.01)	.505
Cross-level interactions										
Network size X Norms									-.00 (.00)	.004**
Network density X Norms									-.09 (.02)	.000***
Network centralization X Norms									.02 (.00)	.008**
Variance component										
Level-2 variance	.82 (.12)		.68 (.10)		.75 (.11)		.68 (.10)		.68 (.10)	
Level-1 variance	.47 (.01)		.47 (.09)		.46 (.09)		.46 (.09)		.45 (.09)	

Note: The dependent variable is the cumulative amount of donations (log). Number of observations is 1488: 62 campaign days in 24 countries.

† = p<0.1, * = p<0.05, ** = p<0.01, *** < p<0.001

Table 4: Overview hypotheses

Number	Hypothesis	Empirical evidence for hypothesis
1	Prosocial norms → Campaign donations	Accepted
2	Network size → Campaign donations	Accepted
2a	Prosocial norms X Network size → Campaign donations	Reversed effect
3	Network density → Campaign donations	Accepted
3a	Prosocial norms X Network density → Campaign donations	Reversed effect
4a	Network centralization → Campaign donations	Rejected
4b	Network decentralization → Campaign donations	Partly accepted, only in interaction with prosocial norms.
4c	Prosocial norms X Network centralization → Campaign donations	Accepted

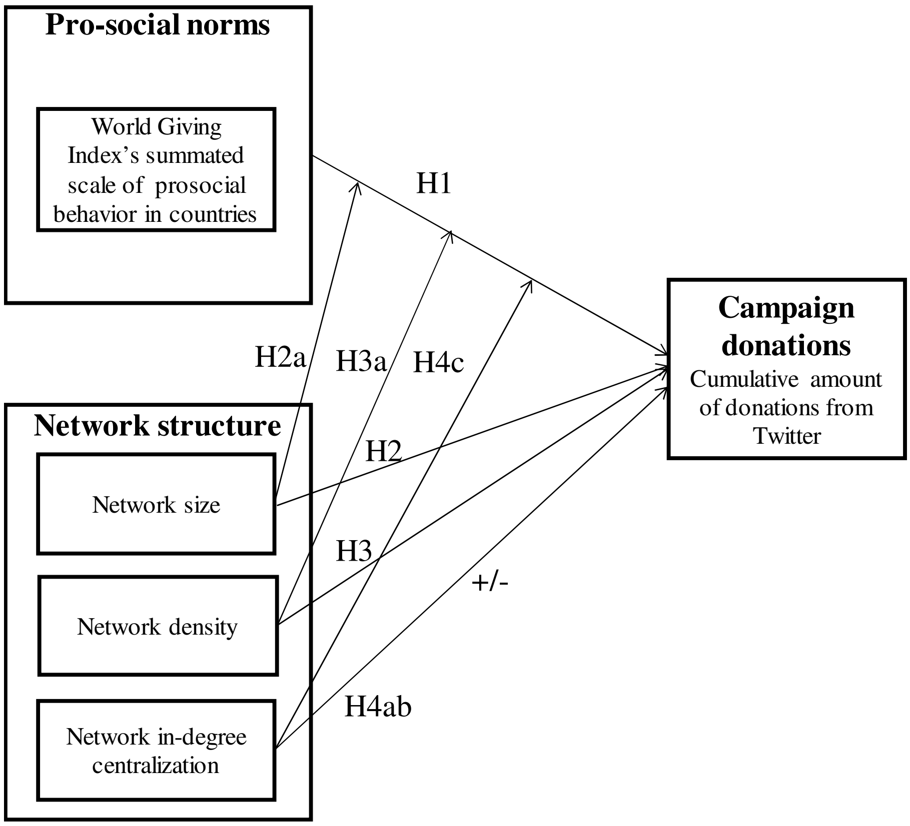

Figure 1: Conceptual model

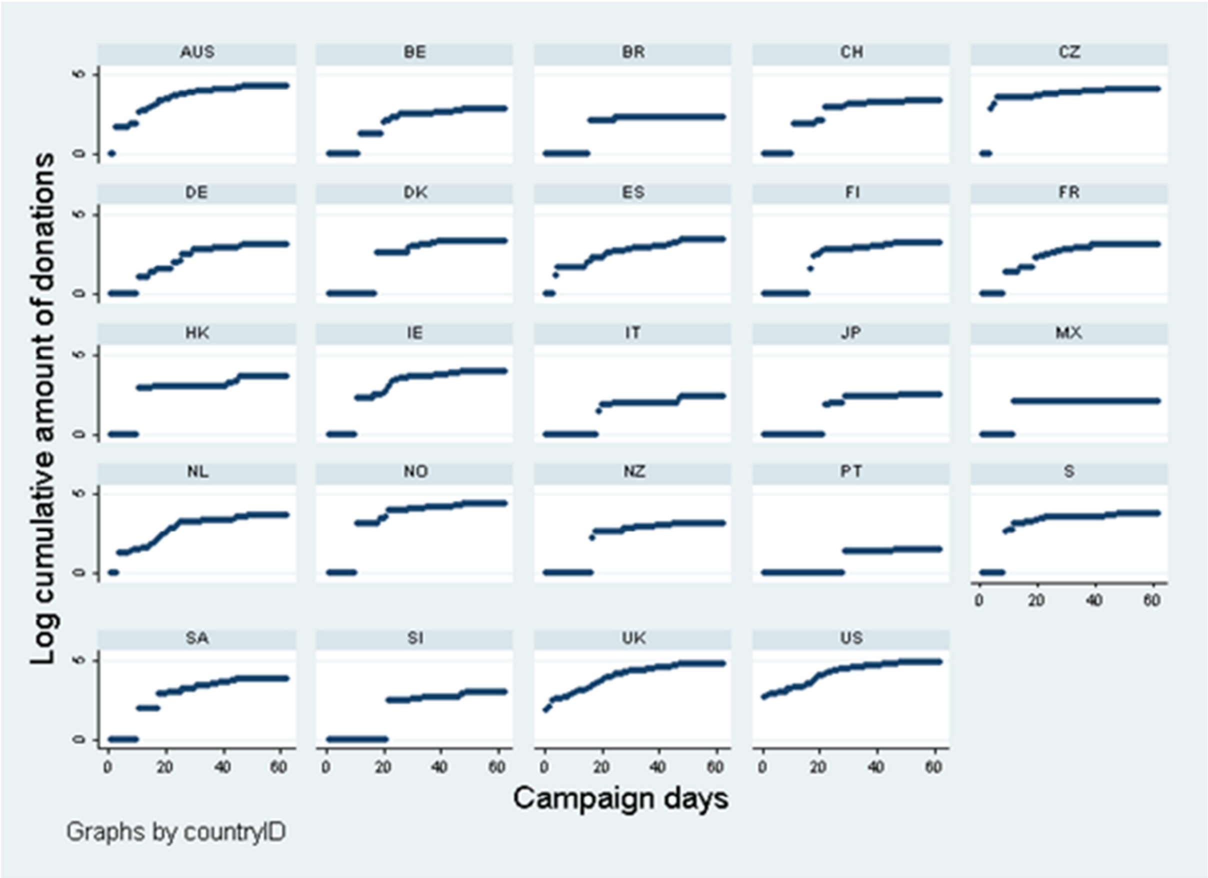

Figure 2: The growth curves of donations during the 2013 Movember Campaign in 24 countries

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