Acquaintance networks and attitudes to climate change.

Arian Borgers[1], Rachel Pownall[1] & Louis Raes[2]

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1. Maastricht University

2. Tilburg University, Department of Economics, Warandelaan 2 5037 AB Tilburg, NL.
Corresponding author: l.b.d.raes@tilburguniversity.edu

Humans are social animals and as such opinions and behaviors are deeply influenced by friends and acquaintances[1, 2]. Attitudes to climate change are no exception and there is an emerging research literature devoted to this topic[3, 4]. This literature is motivated by the idea that addressing natural resource problems, such as climate change, requires an improved understanding of how to overcome collaborative barriers[3, 5, 6]. However empirical research on social networks is complicated, since collecting full network data is often prohibitively costly. In this work, we use an alternative approach to construct a measure of social closeness and collect data in the form of "How many X's do you know?". Using a survey among the Dutch population, we show that being close to people with environmental concerns has a strong influence on a range of attitudinal indicators such as worrying about climate change as well as on actual decisions such as the choice of buying green electricity. These results emphasize the importance of social ties, linking these to beliefs about climate change and pro-environmental behavior.

A consensus is emerging in the scientific community regarding climate change and the role of human activity in global warming[7], although disagreement is prevalent among the general public. A recent study reports that 63% of Americans believe global warming is happening, with county-level estimates ranging from 43% to 80%[8]. In the light of this, researchers have proposed different theories and investigated various determinants of the public perception of climate change.

Risk perceptions and (biocentric) values seem to play an important role in shaping climate change attitudes and behaviors[4, 9]. Similarly, people who have first hand experience of natural disasters (allegedly) related to climate change are more likely to be concerned and alter their behavior[10, 11, 12]. In contrast, scientific literacy does not unequivocally increase climate change concern but seems to strengthen cultural polarization[13]. Related to cultural polarization, some studies show that political orientation influences climate change perceptions and affects the choice of whether to invest in energy-efficient technology[14, 15]. A recent strand of the literature proposes the cultural cognition thesis, stating that individual perceptions of societal risks tend to cohere with values, characteristic of the groups with which individuals identify[13, 16, 17].

This line of research explicitly acknowledges the importance of social ties and connections. Social ties and networks have been found to be crucial in understanding attitude formation and social processes in general[18, 19]. In the context of natural resource problems, social networks are thought to be crucial for effective enforcement and compliance with environmental regulations[3]. A recent study found that ties to environmental movement organization members are correlated with climate change attitudes amongst the general public[4]. However empirical research in this area, employing quantitative analyses of network characteristics, is still scant[3]. A major reason for this is that the majority of statistical methods to analyze social network data assumes that complete network data is available. This requirement is considered to be a major obstacle to research on social ties[20].

In this study, we add to the literature by studying the influence of ties to people with pro-environmental attitudes. Our approach is easy to implement and can be tailored to specific settings. We use answers to questions of the form "How many X's do you know?" where X represents a subpopulation of interest. This type of question was initially proposed to study populations that are difficult to reach[21]. Recent advances in statistics allow us to use answers to these questions to study network features[20, 22, 23]. In particular, we construct a proximity measure capturing closeness to people with pro-environmental attitudes and behavior. This proximity measure represents the connectivity to these people in excess of what could be expected for a person with a similar network size[20, 22].

We collected data by including a range of questions of the type "How many X's do you know?" to a customized wave of the CentERpanel, a survey maintained by CentERdata, a research institute in the Netherlands. Survey participants were told that: *"Knowing means that you know this person's name and you would give a sign of recognition when you ran into this person. Please limit yourself to people who currently live in the Netherlands and who you expect to be aged sixteen or older."* In principle, one can use different definitions leading to different conceptualizations of one's social network. The definition used here is similar to the literature on the estimation of acquaintance networks[20, 22]. The X's in this study refer to twelve names and the following four characteristics: (i) people who don't eat meat, (ii) people who vote for the Green Party in the election for the House of Representatives, (iii) households owning solar panels, (iv) households owning an SUV. These variables are understood to be related to environmental concerns. The "name" questions ("How many people called Kevin do you know?") serve to calibrate and estimate the model (see the methods section).

We use these count variables to construct a proximity variable. The construction of the proximity variable is a two-stage process. First, we estimate a model of social ties. This model is a general model where the formation of ties (in our case *knowing someone*) is based on (1) one's individual network size, (2) the size of the subpopulation with which ties are formed and (3) the propensity individuals have to form ties with members of that subpopulation. In a second stage, we calculate the differences between the predictions of the model and the observed answers. These differences capture whether someone knows more or fewer members of a certain subpopulation than would have been deduced on the basis of a general model of social tie formation. These proximity variables capture whether someone is close to a certain subpopulation[20, 22]. We have proximity variables for each of the four green categories we consider. We present results from one single proximity index, which is the average of these four proximity variables.

A summary of the model of social ties and the proximity index is presented in Figure 1. The left graph shows the estimated overdispersion parameters. Overdispersion means a higher variability in knowing people in a population than what would be expected from an assumption of random tie formation. High overdispersion can be interpreted as a measure of network segregation[24]. The low overdispersion for all names except for Mohammed (ethnically loaded in the Netherlands) are as expected. The fact that we find higher overdispersion for our four categories suggests that there is some social structure in play. In the right graph we show the distribution of the proximity index. To facilitate the analyses, we cut this index into three terciles and construct dummy variables. The baseline category comprises individuals with low proximity scores; individuals who are not close to people with pro-environmental attitudes and behaviors.

To analyze the importance of being close to people with pro-environmental attitudes on individuals' own attitudes towards climate change, we estimate various multiple regressions. The CentERpanel contains questions ascertaining individuals' attitudes towards climate change, presented in Table 1. Besides these four attitudinal items, we also use a question on the use of green electricity. Green electricity refers to electricity which is produced through renewable resources and relatively close to the end consumer. Studying green electricity brings two advantages. First, there are no obvious fiscal or financial incentives as purchasing green electricity is more expensive than regular electricity in the Netherlands and there are no tax deductions available. In contrast, buying energy efficient boilers could be driven solely by financial considerations. Second, green electricity is not directly observable by peers. As such it is less likely that people procure green electricity as a status signal, but do so out of a genuine environmental concern[25].

As this is a cross-sectional setup, the coefficients should not be given strict causal interpretation. In our regressions, we controlled for gender, age, wealth, education, optimism, household size, relationship status (single or with a partner), the level of urbanization where respondents live, religion, province as well as six psychological traits (the big five personality traits and future consideration[26, 27]). We report the regression results in Table 2. This Table presents the results of estimating the different models by ordinary least squares to facilitate interpretation. The supplemental information file shows the results when estimating these models by means of (ordered) probit as well as various sensitivity checks. Note that most control variables are suppressed in the table to facilitate reading. The full results are provided in the supplemental information file. Besides proximity, we show the coefficients on gender, age, wealth and education.

In columns one to four, we see that respondents in the upper tercile of our proximity measure tend to worry more about climate change, consider themselves more knowledgeable, consider their own behavior more often influential and find it more important to reduce their own global footprint, than respondents in the lower tercile. All these result suggest that being close to pro-environmental people is associated with a higher concern and care about climate change. In the fifth column, we see that respondents in the upper tercile have a substantially higher probability of using green electricity. Note that this item is binary, hence the effect size is large. The results in Table 2 also indicate that higher education has an effect. We explore this further by restricting the sample to highly educated respondents and re-estimating our regression specifications (without education as control variable).

When we consider only high educated respondents, we notice that the estimated effect size increases for most outcome variables. Respondents falling both in the middle and the upper tercile of our proximity measure worry more often, tend to report more that they feel they can influence climate change by altering individual behavior and find a reduction of global footprint more important. In sharp contrast, we find no difference in self-assessed knowledge on climate change within the higher educated group. The effect of using green electricity is even higher than for the general sample. When we restrict our attention to high income individuals, we find results which are very much in line with the results for the unrestricted sample and thus we do not report these results here.

The major finding of this study is that among the general public, proximity to people with pro-environmental attitudes increases an individual's own pro-environmental attitudes and choices. This complements earlier findings which reported on the influence of ties to environmental organizations specifically[4]. In a regression analysis, proximity appears a key predictor for environmental attitudes and choices. This finding holds in subsamples and is robust to alternative specifications and attitudinal indicators. Furthermore we showed that proximity has a large effect on a real choice, the use of green energy.

Understanding how social network structure affects behavior (and actions) may lead to the design of more effective climate change education. A dollar can only be spent once and policy makers might want to devote more resources to target areas or groups where environmental concerns are low[28]. While this paper is silent on the effort required to convince people in such groups or areas, it is the case there is more scope for improvement there. Our results demonstrate that acquaintance networks matter a lot. If people search like minded people this can lead to a positive feedback system. Further research is needed to tease out such a mechanism but our findings at least suggest that effective policy intervention requires affecting sufficient critical mass in the targeted audiences.

This paper focused on acquaintance networks and emphasized the importance of weak ties[29]. Since the approach is flexible and easy to implement, researchers have a powerful tool with which they can easily follow up on this research, focusing on other characteristics or studying closer ties.

Methods

The variable *Proximity* is the variable of interest and is constructed using "How many X's do you know?" questions and an overdispersed Poisson model[22]. We assume that the number of individuals in subpopulation k known to individual i follows a Poisson model: $y_{ik} \sim (a_i b_k g_{ik})$. Here a_i is the network size of individual i or the number of people individual i knows. The parameter b_k is the proportion of all ties in the population that involve subpopulation k. In a world where associations between individuals are randomly made, the expected number of individuals known by individual i would be $a_i b_k$. However individuals differ in their propensity to know people from particular subpopulations. We therefore add the parameter g_{ik}, which allows the individual propensity to know people in a particular subpopulation to vary across individuals. To make this model tractable, we assume that g_{ik} follows a gamma distribution with a mean of 1 and a shape parameter of $1/(\omega_k - 1)$. Setting the mean of the gamma distribution to 1 is inconsequential as this just leads to shifts in the β_k parameters (see below). The shape parameter features ω_k, which is estimated from the data. The parameterization of the shape parameter is convenient as it leads to a negative binomial model $y_{ik} \sim$ Neg. Bin.(mean $= e^{\alpha_i + \beta_k}$, overdispersion $= \omega_k$) where $\alpha_i = \log(a_i), \beta_k = \log(b_k)$, ω_k scales the variance of the number of ties between individuals and members of subpopulation k as follows: $\text{Var}(y_{ik}) = \omega_k \mathbb{E}(y_{ik})$.

This model is estimated Bayesianly with priors $\alpha_i = \log(a_i) \sim N(\mu_\alpha, \sigma_\alpha^2)$, $\beta_k = \log(b_k) \sim N(\mu_\beta, \sigma_\beta^2)$ and independent uniform$(0,1)$ priors to the overdispersion parameters on the inverse scale. To identify the model, some parameters need to be identified. Following the literature, we have added questions on first names. Because we have administrative data on names in the Netherlands, we are able to pin down these parameters by specifying tight priors around the true values for these[22]. In the choice of these names, we followed the recommendations in the literature to minimize potential biases associated with choosing too common or too uncommon names[23]. Further details are provided in the supplementary information file to this article.

This model is a general model of tie formation and we use this to construct the Proximity variable. To do this we calculate $r_{i,k} = \sqrt{y_{i,k}} - \sqrt{a_i b_k}$. We construct $r_{i,k}$ for the following four subpopulations: people who don't eat meat, people who vote for the Green Party in the election for the House of Representatives, households where at least one person owns solar panels, households owning an SUV. The Proximity measure used throughout is then the average of these four $r_{i,k}$ measures. To facilitate interpretation, we have trichotomized this variable in the analysis.

The supplementary information file contains further results showing the robustness of the results to various sensitivity checks such as: (1) discrete choice regressions (instead of a linear regression), (2) linear regressions with proximity measures based on a single answer category, (3) alternative constructions of the control variables. These sensitivity checks confirm the findings reported above.

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Addendum

Author contributions

This study was designed by author A, B and C. The analysis was conducted by A and C. All authors contributed to the writing of the manuscript.

Additional information

Supplementary information is available online.

Competing Interests

The authors declare that they have no competing financial interests.

Correspondence

Figure 1 Graphical summaries of the overdispersed model. Graph (a): the overdispersion parameter for each subpopulation of interest. Graph (b): a histogram showing the proximity index.

Table 1: Questions assessing attitudes on climate change

Variables	Description	Obs.	Mean	S.D.
Worry	Do you ever worry about climate change? From 1 (no, absolutely not) to 4 (yes, certainly).	2065	2.589	.744
Knowledge	To what extent are you familiar with the possible consequences of climate change? From 1 (not familiar at all) to 4 (very familiar).	2065	2.230	.584
Influence	How much influence do you think your own behavior has on climate change? From 1 (no influence at all) to 4 (a lot of influence).	2065	2.463	.690
Reduce	How important is it to you to reduce your global footprint? From 1 (not important at all) to 5 (very important).	1904	3.829	.900
Green elec.	Do you use so-called "green" electricity? Binary item: 0 (no) and 1 (yes).	1403	0.520	.500

This Table shows items on attitudes towards climate change and the use of green electricity. The full sample contains 2065 individuals. For some items, we have less than 2065 observations, due to item non-response but mostly due to individuals answering "I do not know" treated as missing observations. For the question on green electricity we have fewer observations because we combined an older wave to our questionnaire and lost some respondents who rotated out of the sample.

Table 2: Regression results

VARIABLES	(1) Worry	(2) Knowledge	(3) Influence	(4) Reduce	(5) Green elec.
Proximity Mid	0.056	0.106***	0.054	0.055	0.078**
	(1.336)	(3.399)	(1.339)	(0.966)	(1.978)
Proximity High	0.234***	0.146***	0.172***	0.243***	0.157***
	(5.246)	(4.294)	(4.114)	(4.368)	(3.803)
Male	-0.025	0.170***	-0.172***	-0.019	0.024
	(-0.633)	(5.551)	(-4.646)	(-0.390)	(0.637)
Age	0.003**	-0.001	-0.004***	0.003*	-0.001
	(1.966)	(-0.788)	(-2.918)	(1.830)	(-0.888)
Total assets (Ln)	0.007	0.004	0.007	0.012	0.001
	(1.168)	(0.808)	(1.127)	(1.591)	(0.105)
Education	0.038***	0.018*	0.026**	0.047***	0.006
	(2.724)	(1.688)	(1.972)	(2.594)	(0.446)
Constant	1.379***	0.926***	1.680***	2.433***	0.289
	(5.893)	(5.047)	(7.893)	(8.210)	(1.362)

Standard errors are heteroskedasticity robust. T-stats are given within parentheses. Asterisks mark p-values: $* < 0.1, ** < 0.05, *** < 0.01$. The regression models contain more control variables but these are suppressed in this Table. Full regression results as well as sensitivity tests are provided in the supplementary information file. This table presents results for linear probability models (classical linear regression). In the supplementary information file, we show the results when estimating these models by means of (ordered) probit.

Table 3: Regression results: sample restricted to university educated respondents

VARIABLES	(1) Worry	(2) Knowledge	(3) Influence	(4) Reduce	(5) Green elec.
Proximity Mid	0.45***	-0.14	0.31**	0.26	0.07
	(0.14)	(0.11)	(0.14)	(0.20)	(0.13)
Proximity High	0.52***	-0.02	0.32***	0.57***	0.19*
	(0.13)	(0.11)	(0.12)	(0.17)	(0.11)

Standard errors are heteroskedasticity robust. T-stats are given in parentheses. Asterisks mark p-values: $* < 0.1, ** < 0.05, *** < 0.01$. The regression models contain more control variables but these are suppressed in this Table. Full regression results as well as sensitivity tests are provided in the supplementary information file.