The Influence of Social Relationships on Pro-Environment Behaviors

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Abstract

We examine how social relationships are related to pro-environment behaviors. We use new data from a nationally representative U.S. sample to estimate latent cluster models in which we describe individuals' profiles of social ties with family, neighbor, and coworkers along two dimensions: intensity of connections and pro-environment norms. While our results confirm the link between social ties and economic behaviors, we show that ties among relatives, neighbors, and coworkers are not perfect substitutes. In particular, we observe consistent relationships between green family profiles and altruistic and community-based behaviors. We also find that the effect of coworker ties is visible for cost-saving activities and altruistic behaviors, and that neighbors matter for working with others in the community to solve a local problem, volunteering, and recycling.

Key Words: Pro-environment behaviors, social relationships, latent cluster models

1. Introduction

Individuals make decisions embedded in a social context. Social scientists have explored the links between social relationships and behavior and there is now substantial and growing evidence that social ties influence beliefs, values, preferences, and choices (Alesina and Giuliano [2], Kurz, Linden, and Sheehy [22], McCallum, Hughey, and Rixecker [26], Akerlof and Kranton [1], Manski [24], Glaeser, Sacerdote, and Scheinkman [16]; among others).

In this paper, we analyze new data from a nationally representative U.S. sample to examine whether and how social ties relate to behaviors that determine a household's carbon footprint. We take a novel approach to describe a person's social ties. We consider two aspects of social relationships: (1) the intensity or strength of ties that we proxy by the number and frequency of social contacts, and by closeness and trust with relatives, neighbors, and coworkers;[1] and (2) the extent of pro-environment norms among an individual's social ties. Then, we apply latent cluster models to these indicators of norms and strength of ties to estimate individual profiles of social relationships.[2]

Using the results of the latent cluster models as independent variables in probit models, we estimate how differences across social profiles correlate with differences in the likelihood that people engage in pro-environment behaviors, after controlling for other individual characteristics. We find that individuals whose social contacts hold pro-environment norms are more likely to engage in pro-environment behaviors. We do not find evidence that that the strength of ties by itself explains pro-environment behaviors. We also show that whether "green"

[1] In this paper, strength of ties signifies the intensity of relationships. In the social capital and social network literatures, the concept of strong ties is typically used to design connections with family and close friends, while weak ties refer to connections between friends, coworkers, and such (Granovetter [17]).

[2] We refer to the output of latent cluster models as "profiles." We avoid the term "network" because individuals described by the same profile are not connected among themselves. Rather, individuals with the same profile are connected with similar intensity to their own relatives, neighbors, and coworkers; and those relatives, neighbors, and coworkers hold similar norms about the environment.

ties exist among relatives, neighbors, or coworkers matter differently for different behaviors. In particular, individuals characterized by a profile of green family ties are more likely to engage in altruistic and community-based behaviors; individuals with a profile of green ties among coworkers are more likely to undertake cost-saving activities and altruistic behaviors; and individuals with a green neighbor profile are more likely to engage in community-based behaviors.

These results offer a nuanced view of how social ties matter for economic decisions. It is important for policymakers and researchers to acknowledge whether and to what extent social relationships are a source of heterogeneity in behaviors as public policies might be designed and implemented to exploit the beneficial impact of social factors, what Thaler and Sunstein [38] call social nudges.

We perform robustness checks to address the potential problems we face when we interpret our results. First, it is possible that there are confounding variables that simultaneously influence behaviors and social relationships. We address this problem by adding several control variables that are likely to capture incentives to engage in pro-environment activities and seek out like-minded individuals. A second issue is reverse causality: individuals who engage in pro-environment activities may seek out social relationships with other pro-environment individuals. Although we cannot rule out reverse causality conclusively, we show that our results hold even when we use a sub-sample of individuals for whom reverse causality is a priori less of a problem (individuals who do not define themselves as environmentalists). In addition, we find that individuals whose relatives hold pro-environment norms are more likely to engage in pro-environment behaviors. Since people have a limited choice about who their relatives are, these findings suggest that causation may run from social ties to behavior. Finally, responses to one of our indicators of social ties may suffer from projection bias: respondents may believe that others behave as they do when it is not the case. Although the latent cluster model estimation method allows us to assume that we measure indicators with error, we also show that when we eliminate the indicator that relies on proxy reporting, our main conclusions are unchanged.

To confirm the validity of our classification of social ties, we present additional evidence. First, we estimate a model for life satisfaction. We should find that, on average, differences in the strength of social ties matter for self-reported life satisfaction but that pro-environment norms do not. As expected, we find that individuals with numerous ties and frequent contact with others show higher self-reported life satisfaction, independent of the level of greenness among their relatives, neighbors, and coworkers. Second, we show that the different results for family, neighbor, and coworker groups are robust to an alternative specification that includes a dummy variable that equals one if the respondent is characterized by *any* green profile.

Although our results are consistent with the argument that social ties influence behaviors, it is important to note that we cannot prove causality. The challenges of identifying social influences are well-researched in the literature. Manski [25] shows that endogenous effects where individual behavior changes with group behavior can be estimated only under strong parametric assumptions. While Manski considers the influence of average group behavior, researchers have also considered whether it is possible to identify the effects of social influence from individuals within a social network. In particular, there is debate about the identification strategies and inferences in the work by Christakis and Fowler [9, 14] on the transmission of health outcomes and subjective well-being within social networks. For example, Shalizi and Thomas [35] show that social influence effects and assertive-mixing (self-selection) effects are typically confounded and that the estimation strategies Christakis and Fowler have adopted might not suffice to separate between these effects. Although our approach consists of estimating the relationship between an individual characteristic (social profile) and individual behavior rather than the influence of group effects as in Manski [25] or of others' behavior as in Christakis and Fowler [9, 14], we build individual social profiles from indicators of social networks. Thus, we must make modest claims regarding causal effects.

The rest of the paper is organized as follows: Section 2 briefly presents our work in the context of the research program on social relationships and economic outcomes. Section 3 discusses the conceptual framework that motivates our hypotheses. Section 4 presents the survey design. Section 5 discusses the latent cluster models and their results. Section 6 discusses the results of models linking social relationships to pro-environment behaviors. Section 7 concludes.

2. Literature Review

The economics research program on social influences is extensive. In order to distinguish our paper from previous work, it is useful to compare it to social capital research and network analysis.

The literature on social capital focuses on the resources that are available to individuals through their membership in social networks. Researchers have conducted studies at different levels of aggregation using different indicators of social capital. These studies measure the stock of social capital of individuals (or communities or nations) and then estimate the effect of social capital stock on some economic outcome. Typical measures of social capital stock are indices of trust and reciprocity, and memberships in voluntary organizations. (See, among many other references, Knack and Keefer [21], Easterly and Levine [13], Putnam [33], Glaeser, Laibson, and

Sacerdote [15], Guiso, Sapienza, and Zingales [18]. Durlauf and Fafchamps [12] provide a survey and critical analysis of this literature.)

Network analysis examines the social structure formed by the ties between each person (the ego) and all other individuals (the alters) in the network. Network analyses have examined the formation and properties of networks and how information is transmitted within a network, how networks shape norms, and how networks can influence the economic outcomes of their members.[3] (Munshi [29], Calvó-Armengol and Jackson [7], Bearman, Moody, and Stovel [4], Bandiera and Rasul [3]; Jackson [20] presents the theory of networks and multiple applications in the social sciences.)

Our research relates to the social capital literature because we argue that the information and resources individuals have access to through their networks, and the social norms they follow, influence behavior. We take a more sophisticated approach than is typical in the social capital literature because research on networks informs our assumption that the social structure that generates social capital may matter. That is, the number of ties and intensity of relationships is likely to influence the quality of resources, how information is transmitted, and how norms shape behavior. In addition, while social capital research generally uses one dimension of social capital stock, such as trust or number of group memberships, we account for the multidimensional properties of social ties by estimating social profiles using simultaneously several indicators of the number of ties, intensity of relationships, and norms.

Another area of research we contribute to is the literature on social ties and environmental behaviors. Kurz, Linden, and Sheehy [22] examine how the social context influences recycling behavior and find that a "sense of community" variable explains as much of

[3] Another related area of research is peer effect studies. These models aim to explain how average performance by others influence own performance. This approach requires data for the reference group but not the mapping of ties between each individual and his or her alters.

the variability in individual recycling frequency as attitudes towards recycling do. Miller and Buys [27] find that individuals who report close relationships with neighbors are more likely to engage in a more environment-friendly car-washing mode in a drought-prone community; however, individuals who are more socially proactive are more likely to use weed-killers. The authors argue that this latter finding might suggest that when aesthetics, rather than water conservation, dominate community concerns then communal norms may affect sustainability in a negative way. McCallum, Hughey, and Rixecker [26] investigate six community environmental management initiatives in New Zealand and examine the role that trust and norms and rules play on facilitating cooperation among community members. The authors find that although social capital did influence collaboration, in some cases existing norms were an obstacle for achieving the intended goals. The authors also find that there is variability in terms of the resources individuals have access to within their networks. The work by McCallum, Hughey, and Rixecker and Miller and Buys suggests that researchers need to control for norms, in addition to measures of ties, when estimating pro-environment engagement.

We contribute to this literature by adopting a probability-based approach to measure distinct profiles of social relationships, and by examining three different social groups (neighbor, coworker, and family). Importantly, we consider simultaneously two dimensions of social relationships, norms and strength of ties.

Finally, the work by Charles and Kline [8] shares some assumptions and goals with our paper. Charles and Kline [8] examine how individuals' stocks of neighborhood social capital influence whether they carpool to work. The authors find that the likelihood that an individual carpools increases with the proportion of his neighbors who are of the same race (a measure of their social capital). Although Charles and Kline analyze neighborhood social capital and carpooling only, they hypothesize that "[d]ifferent types of social capital stocks are probably of differential importance in different circumstances." That is, Charles and Kline argue that social capital needs to be considered in the context of "a particular universe" or social group. In our paper we explore this idea that different "universes" or social contexts generate different types and quantities of resources.

3. Conceptual Framework and Hypotheses

There are several reasons why we expect an association between social ties and the likelihood of engaging in pro-environment behaviors. First, how many relatives, neighbors, and coworkers we interact with, and how frequent those interactions are, determine the access to information that is required to evaluate the potential savings from energy-conservation projects, the health benefits from certain consumption choices, or the environmental impact of one's efforts. Second, reliance on relatives, neighbors, and coworkers can reduce the cost of engaging in some pro-environment efforts. Third, to the extent that a person's social context influences the internalization of norms and values, peer pressure and attachment will determine behaviors (Sorensen et al. [37], Durlauf and Fafchamps [12], Passy [32]).

These effects of social ties on pro-environment behaviors are likely to depend on both the strength of ties and the extent of pro-environment norms. As Charles and Kline [8] hypothesize, the effects may also differ according to social group and behavior; for example, since household recycling might be visible to community members, living among neighbors who are environmentally-minded may have a different effect on this behavior than ties with "green" coworkers may.

To formalize these hypotheses, we borrow from the model of moral motivation developed by Brekke, Kverndokk, and Nyborg [5], and the work by Akerlof and Kranton [1] on the economics of identity. Following the model by Brekke, Kverndokk, and Nyborg, we argue that social norms influence the individual's utility and, in particular, that deviating from the norm causes disutility. As in Brekke, Kverndokk, and Nyborg, we also include in our model a parameter that measures how "efficient" a unit of effort is in producing contributions to a public good. Our framework differs from the model by Brekke, Kverndokk, and Nyborg in two fundamental aspects. First, as in the work by Akerlof and Kranton, we assume that there are multiple social contexts with different sets of norms. Second, while in Brekke, Kverndokk, and Nyborg the efficiency parameter measures technical and institutional factors common to all individuals, in our model the parameter varies according to the individual's profile of social ties and reflects the value of access to information and resources that are particular to that profile.[4]

Specifically, we assume that the individual interacts with K different social groups (in our empirical model we consider three social groups: family, neighbors, and coworkers). The individual is characterized by one of J exclusive profiles in each social group, for example, an individual may be characterized by weak ties with neighbors and lack of pro-environment norms in the neighborhood while a second individual might be defined by weak ties with neighbors but prevalent pro-environment norms in the neighborhood. Let $ik(j)$ be individual i's profile j for social group k. Thus, each profile j describes the nature of social relationships within social group k to which individual i belongs. How many meaningful and distinct profiles we can identify in the population is an empirical question that we pursue in Section 5.

[4] We do not attempt to explain how this multiplicity of social relations and norms come to exist, although it is a fact in our data.

For the sake of simplicity, in developing our conceptual framework, we assume that individuals engage in one behavior. (In our empirical implementation, we examine several behaviors.) We define efforts on the activity, in units of time, as *e*. We assume that an individual's utility depends on the consumption of private goods, *x*, the level of the public good, *G*, and the individual's self-image or identity, *I*. An individual's identity depends on how close to the norm the individual behaves. Because the norm depends on the individual's profile of social ties, we specify individual's *i* self-image from belonging to group *k* with profile *j* as follows: $I_{ik(j)} = -\gamma_{ik(j)}(e_i - e^*_{ik(j)})^2$, where $\gamma_{ik(j)}$ is a indicator variable that takes on the value of one if the individual belongs to profile *j* for social group *k*, and takes on the value of zero otherwise; and $e^*_{ik(j)} \geq 0$ is the level of effort for a given activity that is the norm in profile *j* for social group *k*. Note that $e^*_{ik(j)}$ might be equal to zero if the profile indexes weak or no pro-environment norms.

Let g_i be the contribution of individual *i* to the public good. The contribution depends on the effort the individual puts on producing the public good through a given activity and an efficiency parameter that converts effort on that activity into the public good. Let $\theta_{k(j)} \geq 0$ be the efficiency parameter for profile *j* and social group *k* that captures how access to information and resources increases the productivity of one unit of effort.[5] Then, $g_i = e_i \sum_{k=1}^{K} \sum_{j=1}^{J} \gamma_{ik(j)} \theta_{k(j)}$.

The utility function is given by: $U_i = u(x_i, G, \sum_{k=1}^{K} \sum_{j=1}^{J} I_{ik(j)})$ where *G* is the sum of individual contributions. Finally, we assume the time constraint of each individual is

[5] We assume the public good is the sum of contributions across social groups. Alternatively, we could assume the public good is the maximum of contributions.

$x_i + e_i = T$ where one unit of time can be directly converted to the private good. Thus, we can write the utility function as: $U_i = u(T - e_i, \sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{N} e_i \gamma_{ik(j)}\theta_{k(j)}, \sum_{k=1}^{K}\sum_{j=1}^{J} -\gamma_{ik(j)}(e_i - e_{ij(k)}^{*})^2)$.

Since the indicator and the efficiency parameters are fixed given a profile of social relationships, the individual's maximizes utility by choosing the optimal level of effort. If we assume the utility function is additively separable and the marginal utility of the identity argument is equal to one, then it is straightforward to show that optimal efforts increase if the efficiency parameter increases or if the norm increases. This result motivates our first set of hypotheses. Specifically, we expect that individuals who hold social profiles characterized by pro-environment norms are more likely to engage in pro-environment behaviors. Furthermore, since individuals with strong ties are more likely to rely on others, access more resources, and generate the public good more efficiently, we also expect that individuals who hold social profiles characterized by strong ties and pro-environment norms are more likely to engage in pro-environment behaviors than individuals with profiles defined by pro-environment norms but weak ties.

In the previous section we argued that different types of social capital might matter differently for different behaviors. The model above can generate differential effects if we consider that norms and resources are likely to vary across profiles, and that these norms and resources might not be perfect substitutes across behaviors. For example, it is reasonable to expect that norms among neighbors are more important if the activity is visible to neighbors. Similarly, coworkers might be less likely to help reducing the cost of engaging in community-based behaviors than relatives and neighbors are. Whether or not the social ties among relatives, neighbors, and coworkers are perfect substitutes is an empirical question that we explore in Section 6 by estimating the effects of social profiles on different behaviors.

To examine how the likelihood that individuals engage in pro-environment behaviors relates to the types of social ties they hold, we first need to estimate the profile of social ties, that is, we need to classify each individual into a profile for each social group. We estimate latent cluster models and find that there are distinct profiles of social relationships that vary both in terms of the intensity or strength of connections and the prevalence of pro-environment norms. We also find that there is variability in profiles according to social group, that is, an individual with a "green" family profile does not necessarily have a "green" coworker or neighbor profile.

Then we estimate how the profiles of social ties correlate with pro-environment behaviors, after controlling for other individuals characteristics. We examine several behaviors that may be driven by different motivations and for which different social groups may provide different resources: altruistic behaviors (for example, whether or not the individual has donated to an environmental organization), activities that reduce energy costs (having an insulated water heater in the household), behaviors that involve interactions with others (such as working with others in the community to solve a local environmental problem), and activities that are likely to depend on social norms (such as recycling). Section 6 discusses the dependent variables in detail.

4. Survey Design

We use new data from a sample of U.S. households. Knowledge Networks administered the survey in August 2009 as an off-wave of the American National Election Studies (ANES) panel. Knowledge Networks recruited the panel via random digit dialing.[6] The surveys are approximately 30 minutes in length and are completed on-line. Sixty-three percent of the individuals who were contacted completed the survey. We supplemented the ANES off-wave

[6] Respondents were offered $10 per month to complete monthly surveys. Individuals who did not have access to the Internet were offered a web appliance and free Internet access during the survey period.

with 2009 data for 450 responses from a sample that we had queried about environmental behaviors and attitudes in October 2007. For this sample Knowledge Networks also recruited the panel via random digit dialing. In this case, 746 individuals were contacted and 452 completed the survey. We have estimated our models controlling for sample source and found that there is no evidence of differences on mean responses across the two samples for the behaviors we examine.

The survey instrument elicits responses about pro-environment behaviors, attitudes towards the environment and public policies; social networks; changes in life circumstances; and the influence of religion and religious affiliations on environmental behaviors and attitudes.[7]

Responses to the pro-environment behavior questions are comparable to responses from other surveys. For example, only 14 percent of our sample recycles less often than several times a year and 17 percent contributed to an environmental organization in the last 12 months. In the third wave of the World Values Survey, 14 percent of the respondents from the U.S. indicate that they do not recycle and 25 percent say they have contributed to an environmental organization (time frame not specified).

5. Latent Cluster Model: Method and Results

In our conceptual model, the resources individuals have access to and the norms that influence them depend on the particular social network they are part of. Although we do not observe individuals' social networks (a mapping of links between each respondent and all his or her relations), individuals in our survey respond to several questions about relationships and pro-environment norms that are indicators of the properties of their social network. Our goal in this

[7] We tested a subset of the questions on a sample of 200 individuals and two experts reviewed the questionnaire and results from the pilot sample. The questionnaire and tabulation of responses are available at: http://www.hamilton.edu/levitt/Sustainability/Environmental_survey_2009.html

section is to use such indicators to estimate the respondents' social profiles along two dimensions: intensity or strength of ties and norms. To accomplish these goals, latent cluster modeling is an appropriate method both from a conceptual standpoint and practically.

Network membership is a discrete variable and the resources and norms that are relevant for an individual's utility-maximization problem depend on which network the individual belongs to. Thus, we are assuming there is a finite number of discrete profiles – in our conceptual framework, profile *j* for social group *k* – and that each profile entails a set of resources and norms – in our framework, $e^{*}_{k(j)}$ and $\theta_{k(j)}$. Latent cluster models are consistent with this conceptualization of social ties because the method assumes there is a latent variable (social profile) with a finite set of values.

Estimating latent cluster models has also clear practical advantages. On the one hand, we want to use as much relevant information as possible. On the other hand, we need to be parsimonious in our models and also avoid collinearity issues. The indicators of relationships and norms are correlated and measured with error, particularly in the case of the indicator that relies on proxy reporting. Using the indicators separately is likely to create collinearity problems and it might bias estimates. An alternative approach would be to create an index of norms and an index of ties for each social group, and include the indices and their interaction. We have explored this approach and there is also evidence of collinearity. Latent cluster methods allow us to use all relevant information and account for the fact that the variables we use to describe social profiles are indicators with error of an unobservable latent variable.

In sum, we consider a person's social profile an unobserved discrete latent variable and treat the responses to questions about social ties and norms as indicators with error of that unobserved latent construct. The basic idea of a latent cluster model is that the probability of a specific response pattern is the average probability of the response pattern given each class or profile, weighted by the prior probability of profile membership (Magidson and Vermunt [23]).[8]

Let i = 1,…, I, denote the respondents. For each individual we observe the response to a set of indicators for each social group (family, neighbors, and coworkers). Let the vector $\mathbf{Y}_i$ represent the response pattern of an individual to each of the v indicators for a particular social group. We assume a finite number of social profiles denoted j = 1,…, J. The discrete latent variable x represents the profile. Then:

$$P(\mathbf{Y}_i) = \sum_{j=1}^{J} P(X_i = j_i) \times \prod_{v=1}^{V} P(Y_{iv} \mid X_i = j),$$

where the probability that individual i holds profile j:

$$P(X_i = j) = \frac{\exp(\eta_j)}{\sum_{j'=1}^{J} \exp(\eta_{j'})},$$

where:

$$\eta_j = \log\left(\frac{P(x = j)}{[\prod_{j'=1}^{J} P(x = j')]^{1/S}}\right) = \gamma_{j0}$$

and the gamma term is a free parameter.

Latent cluster analysis determines the smallest number of profiles (or classes, or clusters, in standard latent class models terminology) that account for the observed relationships among indicators. We first assume one class – independence among response variables – and then increase the number of classes. To determine the number of latent classes among the models that fit the data, we use the Bayesian information criterion (BIC) based on the model's log-

[8] Recent applications in the economics literature of latent models (also known as finite-mixture models) include Clark, Etile, Postel-Vinay, Senik and Van der Straeten [10], Scarpa and Thiene [34], Morey, Thacher, and Breffle [28], and Owen and Videras [30, 31].

likelihood.[9] We fit the models using Maximum Likelihood methods and sampling weights. The results yield the conditional response probabilities for each indicator. We compare these conditional probabilities to interpret the profiles. Applying Bayes rule, we assign a posterior probability of membership in each class to each individual. We then use these membership probabilities in models estimating the likelihood that the individual engages in several pro-environment behaviors.

We use several variables that are indicators of the strength of connections and the "greenness" of an individual's social ties. To measure the intensity or strength of ties we use responses about frequency of contacts, trust and sense of belonging, and friendship with family members, neighbors, and coworkers. To measure pro-environment norms we use whether the respondent believes that others in the group do things to help the environment and the frequency with which people in the group discuss specific issues about the environment. Tables A1, A2, and A3 in the appendix present the questions and frequency of responses for the indicators of family, neighbor, and coworker profiles. For each social group we estimate separate latent cluster models that include indicators of ties and norms for that group.[10]

Table A4 presents the fit statistics for the latent cluster models. For all groups, a model with two or more profiles fits the data better than the model that assumes a homogeneous population. Using the Bayesian information criterion (BIC) based on the model's log-likelihood, we select the four-class model for family ties and three-class models for neighbors and coworkers ties.

[9] The Bayesian information criterion is calculated as –LL+Ln(N)*P, where -LL is the model's Log-likelihood, P is the number of parameters, and N is the number of observations.
[10] We also estimated latent cluster models that include indicators for all social groups. The models are more complex and the sample size is smaller. As a consequence, the models are less stable.

Table A5, A6, and A7 present the conditional probabilities for each model. Table A5 shows the results for family ties. There are two profiles defined by strong family ties but different environmental norms: individuals in profile 1 are unlikely to think most of their relatives do things to help the environment and they are also unlikely to discuss environmental issues while individuals in profile 2 have the highest conditional probabilities for these two indicators of norms. The other two classes have weaker ties and norms that follow the previous pattern of pro-environment norms (profile 3) and no norms (profile 4).

For neighbors, we select the three-profile model. Individuals in profile 1 have weak ties with neighbors and the lowest conditional probabilities on the two indicators of norms. Individuals in profile 2 have the strongest ties, are the most likely to think most of their neighbors do things to help the environment, and have medium probability in discussing environmental issues. Individuals in profile 3 have medium-strength ties (but low probability of trusting their neighbors a lot), are the most likely to discuss environmental issues with neighbors, and have medium probability of thinking most of their neighbors do things to help the environment. The profiles for coworkers are qualitatively very similar to the types of neighbor networks. Table A8 summarizes the profiles qualitatively. We label the profiles to summarize their probability structure and to provide a quick intuitive description of the differences across profiles.[11]

Based on these results and applying Bayes rules, we assign to each individual a posterior probability of membership for each profile and social group. Using the largest posterior probability to classify individuals to one profile for each social group, we find that there is substantial variability of individual profiles across groups. For example, 56 percent of

[11] As Skrondal and Rabe-Hesketh [36] indicate, we need to interpret the results of latent cluster models as useful hypothetical constructs, in the same way that “social class” or “market segment” are hypothetical constructs.

individuals classified in a green family profile are also characterized by a green neighbor profile and 58 percent of respondents with green coworker profiles are defined by a green neighbor profile. More overlap occurs between family and coworker profiles: 66 percent of respondents in a green coworker profile are also characterized by a green family profile. These statistics suggest that distinguishing across social groups might be useful as individuals do not necessarily have the same profile across all groups.

6. Social Networks on Pro-Environment Behaviors

In this section, we use the estimated posterior probabilities from the latent cluster models to examine whether the likelihood to engage in pro-environment behaviors is associated with an individual's social profile. First, we discuss the dependent variables and control variables. Second, we estimate models for seven specific behaviors that individuals may undertake for different reasons. We also consider a larger set of activities by creating counts of six different cost-saving behaviors and four altruistic behaviors. Third, we perform a series of robustness checks to explore whether reverse causality and projection bias might affect our results, and to provide further evidence of the validity of the latent cluster model's classification.

6.1 Dependent and Independent Variables

We estimate models for seven behaviors to explore whether social relationships have different effects on behaviors that individuals may undertake for different reasons: donations to environmental organizations (DONATE), purchasing fair-trade products (FAIR), having an insulated water heater (HEATER), working with others on the community to solve a local environmental problem (COMMUNITY), volunteering to an environmental project

(VOLUNTEER), recycling cardboard packaging or paper (RECYCLING), and investing in socially-responsible funds (FUND). RECYCLING is equal to one if in the last 12 months the respondent has personally recycled cardboard packaging or paper almost daily, and is equal to zero if the respondent has recycled less often. The other variables are equal to one if the respondent has undertaken the corresponding behavior in the last 12 months, and are equal to zero otherwise. Table 1 presents statistics for the variables.

All models include controls for gender, age and age squared, educational attainment, employment status, household size, and marital status. The models also include regional dummies and dummy variables for income (above $35,000) and homeownership. In addition, the model for RECYCLE includes whether the respondent's local community has a recycling program (as reported by the respondents). The models use sampling weights.

Motivated individuals who are concerned about the environment are likely to engage in pro-environment behaviors and to seek out other concerned individuals. Thus, it is important to control for potential confounding factors. Our models include attitudinal variables that are likely to capture incentives to act pro-environment and have ties with pro-environment individuals. The survey asks individuals whether they consider themselves to be environmentalists. From the responses to this question, we construct GREEN_SOME and GREEN_DEF indicating those who responded "yes, somewhat" and "yes, definitely," respectively. The variable FATALIST[12] equals one if the individual strongly agrees or agrees that it is "difficult for somebody like me to do much about the environment." On a scale of one to four, PERSONAL indicates the extent to which people believe that climate change will affect them personally. We also calculate a proxy for social responsibility by summing the responses to questions about how justifiable it is to cheat on taxes, ride public transportation without paying the fare, download copyrighted music

[12] This variable may also capture free-riding attitudes.

or movies without permission, and buy stolen goods. Respondents state on a scale of one to ten where a ten indicates that the behavior can "never be justified" while a one indicates that the behavior is "always justifiable."[13] The sum of these responses we denote CIVIC. Table 1 shows descriptive statistics for these controls.

6.2 Results

Table 2 presents marginal effects for the base models excluding social profiles. Declared environmentalism and environmental attitudes are generally related to the likelihood of engaging in pro-environment behaviors. Everything else equal, homeowners are on average more likely to undertake some of the behaviors (in particular, having an insulated heater); higher levels of education correlate positively with the likelihood of working with others in the community, volunteering, and purchasing fair-trade products; high-income individuals are also more likely to purchase fair-trade products and invest in socially responsible funds while larger households are less likely to engage in these two behaviors; and women are less likely to work with others in the community and have an insulated heater. These results hold when we add social profiles.

Next, we include in the model social profiles. In particular, we add the posterior probabilities of membership in each cluster, where each cluster represents a profile of social ties. For each social group, the default is the probability of membership in the low connection and low greenness cluster.

Table 3 presents marginal effects for the behaviors when we control for socio-demographic factors, attitudinal variables, and regional dummies; and add profiles for family,

[13] These questions and scales of responses are similar to ones that appear in the World Values Survey.

neighbors, and coworkers.[14] Everything else equal, individuals who are characterized by a green family profile are more likely to donate than individuals whose relatives do not share pro-environment norms, independently of the strength of ties. There is weak evidence that people with coworkers are more likely to donate. We do not find consistent evidence that relationships with neighbors matter.[15]

Regarding recycling cardboard packaging or paper almost daily during the last year, there is weak statistical evidence that relationships with neighbors matter: individuals who have strong connections with neighbors and who think most of their neighbors do things to help the environment are more likely to recycle (at the 10 percent level). The estimate for the profile describing green family networks with strong connections is also statistically significant at the 10 percent level.

The results for working with others in the community to solve an environmental problem show that a green neighbor profile is consistently and strongly significant, in particular, if neighbors discuss frequently environmental issues. For this behavior, the estimate on the profile for green relatives with strong connections is statistically significant at the 5 percent level.

In the case of a behavior related to energy savings, we find statistical evidence that higher probability of holding a green coworker profile is correlated with the household's having an insulated water heater. In particular, the marginal effect of being described by a profile of coworkers who discuss frequently environmental issues is statistically significant at the five

[14] We also estimated models in which we enter probabilities for each social group independently (results available upon request). However, for these specifications the estimates are likely to capture overall strength of ties and overall prevalence of norms, rather than the effect of a given social profile. We focus on consistent effects across specifications.

[15] We obtain very similar results for DONATE when we exclude from the estimation sample individuals who belonged to an environmental group in the last 12 months, except the estimate on coworker network is no longer statistically significant at the 10 percent level.

percent level. On the other hand, the type of family relationships does not correlate with this behavior and the effect for neighbors is significant at the 10 percent.

Finally, strong connections with green coworkers and having pro-environment relatives increases the likelihood of purchasing fair-trade products and investing in socially-responsible funds, everything else equal. Consistent with the results for COMMUNITY, relationships with neighbors who discuss frequently environmental issues is strongly correlated with volunteering.

Comparing across behaviors, we find different effects according to the type of social group. Individuals characterized by a profile of green family ties are more likely to engage in altruistic and community-based behaviors; individuals with a profile of green ties among coworker are more likely to undertake cost-saving activities and altruistic behaviors; and individuals with a green neighbor profile are more likely to engage in community-based behaviors (this result is reasonable as strong green neighbor networks are likely to impact the costs of coordination and highlight social pressures, Burn [6]).

We continue exploring how different social ties may serve different purposes by constructing an index that adds up the following cost-saving behaviors: having an insulated heater, having a programmable thermostat, putting on an extra layer of clothing instead of turning up the heat, buying compact fluorescent light bulbs, unplugging the cell phone charger when not using it, and running the dishwasher or washing machine without a full load less often than several times a year. The most common response is four behaviors (28 percent of the responses). The results of OLS and Poisson models show that respondents holding green family and coworker profiles do engage in more cost-saving activities.

We also estimated OLS and Poisson models for the number of purely altruistic behaviors: purchasing green power, purchasing carbon offsets, donating to environmental organizations, and purchasing fair-trade products. The most common response is zero (65 percent of the observations). In terms of the direction of the effects, the findings are similar to those of the model for donations and fair-trade products. The largest effects on altruistic behaviors are due to green norms among relatives.[16]

6.3 Robustness Checks

A potential problem with the interpretation of results is reverse causality. Reverse causality would affect the results if individuals undertook a given behavior for reasons unrelated to their social ties and, as a consequence of engaging in that behavior, they became connected to other people who discuss environmental issues frequently and do things to help the environment, or, as a consequence of engaging in that behavior, they influenced other people to discuss environmental issues frequently and do things to help the environment. Because we use cross-sectional data we cannot rule out the possibility that reverse causality is driving our results. However, we argue that reverse causality is less plausible among individuals who define themselves as non-environmentalists. Reverse causality for a non-environmentalist would imply an unlikely chain of events in which individuals would undertake a given activity for some personal reason and, as a consequence of that action, they would seek out individuals who share pro-environment norms or would motivate other people in their network to have pro-environment norms, without declaring themselves to be environmentalists. On the other hand, causality would imply that even non-environmentalists who interact with family members, neighbors, or coworkers who are pro-environment may contribute due to access to valuable

[16] These results are available from the authors upon request.

information or peer pressure and sense of belonging to the group.[17] Therefore, if we find statistically significant effects even among a group of non-environmentalists, the results would suggest the more plausible causal story.

Table 4 presents these results for the sub-sample of non-environmentalists. Approximately 26 percent of non-environmentalists are described by green coworker profiles, almost 38 percent by a green neighbor profile, and almost 29 percent by a green family profile. We find that ties with pro-environment relatives still matter for donations, purchasing fair-trade products, and investments in socially-responsible fund; ties with green neighbors relate to COMMUNITY and VOLUNTEER; and ties with green coworkers matter for HEATER, FAIR, and FUND.

A second potential problem is projection bias. One of the indicators of pro-environment norms we use to measure an individual's social ties is the respondents' perception of how many of their relatives, neighbors, and co-workers do things to help the environment (proxy reporting). Although proxy reporting is common in network studies, it is possible that respondents believe others to behave as they do themselves when that is not the case. This would introduce measurement errors and a statistically significant effect of social ties on behavior might be due to the respondents projecting their own behavior onto others (Hogset and Barrett [19]). Testing whether projection bias affects the results would require "snowball sampling," that is, identifying and observing the behavior of each respondent's relatives, neighbors, and co-workers. Because we do not have access to these data, we cannot show whether projection bias influences the results. However, we argue that this issue is likely mitigated by the approach we take to identify an individual's profile of social relationships. In particular, when we estimate latent cluster

[17] In a recent paper, Dellavigna, List, and Malmendier [10] conducts an experiment that shows social pressure increases donations.

models we are assuming that all indicators, including the indicator based on proxy reporting, are measured with error. In addition, we identify an individual's social ties using several indicators of which only one indicator relies on proxy reporting. Nonetheless, to investigate whether the use of a proxy reporting variable affects our results, we estimate latent cluster models for each social group without the indicator of how many relatives (or neighbors or coworkers) do things to help the environment.[18] We find that for neighbors and coworkers, the models that best fit the data parsimoniously are still three-cluster models. In addition, the cluster size and probability structure of the clusters are very similar to those we estimated before. Thus, for neighbors and coworkers excluding the proxy reporting variable does not affect the profiles. When we estimate family profiles, the best model now is a three-cluster model rather than a four-cluster model.[19] When we estimate probit models with the new classification of individuals to profiles, we find that a green family profile matters for donations but does not for the other behaviors. Thus, the link between altruistic behaviors and being characterized by a green family profile still exists but it is not consistent across all altruistic behaviors. The coefficients on the coworker and neighbor profiles are qualitatively very similar. Overall, excluding the proxy reporting variable from our analysis does not affect our main insights.

To check the validity of the latent cluster model's classification, we estimate OLS models for self-reported life satisfaction. We hypothesize that the strength of connections are related to life satisfaction but green norms within a network are unlikely to matter. Table 5 shows the results. As we expected, individuals who hold strong ties with neighbors and coworkers report higher levels of life satisfaction, everything else equal, than individuals in networks with weak or medium social ties, independently of the pro-environment norms. Although differences in family

[18] We estimate the models using the estimation sample in Table 3.
[19] The new profile 1 is an "average" of previous profiles 1 and 2.

profile do not seem to explain life satisfaction (positive but statistically insignificant coefficients on profiles with strong connections in the model with family profiles only), the intensity of ties by itself is statistically related to life satisfaction: when we estimate a model of life satisfaction that includes an index of family ties (the sum of responses to the indicators about ties with relatives), we find that family ties are positively correlated with life satisfaction.

We also explore whether the different results we find for family, neighbors, and coworkers might be an artifact of distinguishing across social groups and whether what matters is that the individual is embedded in any green network. As a robustness check, we estimate the models that include all social groups and a dummy variable that equals one if the respondent's largest posterior probability corresponds to any green profile. In this way, the group-specific posterior probabilities pick up the effect of being classified in each specific profile after controlling for being classified in any green profile. We find the coefficient estimates on posterior probabilities barely change in terms of magnitude and statistical significance.

We also examine whether collinearity due to correlation among profiles and controls might influence the signs and magnitudes of the coefficient estimates on the posterior probabilities. When we estimate models that include only a subset of controls – education, age, and dummy variables for region, gender, high-income group, and race/ethnicity – we find that the signs of the profile variables do not change in any case and that magnitudes are generally greater. We also estimate models that include only the profiles and find that the signs of statistically significant coefficients do not change and that many of the variables remain statistically significant. In sum, these results are corroborating evidence of the validity of our social network classification.

7. Summary

Policymakers can design public policies that rely on the beneficial impact of social factors (Thaler and Sunstein [38]). Thus, it is important for researchers to examine whether and to what extent social relationships generate heterogeneity in behaviors. Our paper offers a nuanced view of how social ties matter for economic decisions, in particular, for behaviors that influence households' carbon footprint.

We use new data from a U.S. nationally representative sample to estimate latent cluster models in which we identify an individual's profile of social ties with family, neighbors, and coworkers. We find that the profiles differ in the intensity of connections and "greenness," and that pro-environment norms among one's ties are positively correlated to pro-environment behaviors. In particular, we observe consistent relationships between green family profiles and altruistic and community-based behaviors. We also find that the effect of coworker ties is visible for cost-saving activities and altruistic behaviors, and that neighbors matter for working with others in the community to solve a local problem, volunteering, and recycling. Thus, while our results confirm the link between social ties and economic behaviors, we also show ties among relatives, neighbors, and coworkers are not perfect substitutes.

Because we use cross-sectional data, we face two issues: confounding variables and reverse causality. To address the first problem, we control for several attitudinal variables that are likely to capture incentives to engage in pro-environment activities and to seek out or influence other people to become "green." Regarding reverse causality, we show that there are statistically significant correlations between social network membership and behaviors for a sub-sample of non-environmentalists for whom reverse causality is less of a problem. Our main results also hold when we drop an indicator of norms that relies on proxy reporting. We also note that given that we rely on observational data, we face challenges in identifying causality similar to those identified in the literature on social influences (Manski [25], Shalizi and Thomas [35]).

Future research may examine whether the effects of socio-economic and attitudinal variables may differ according to social profile, that is, whether there are differential slope effects for social profiles.[20] Future research would also benefit greatly from panel data. Panel data would allow us to control for unobservable individual-specific factors and examine how exogenous shocks to networks can explain changes in behaviors.

[20] We did explore this approach by estimating jointly latent-class membership and likelihood of engaging in the behaviors. However, the models are complex and the results indicated that the models were not attaining a global maximum.

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Table 1: Descriptive Statistics

Dependent Variables		
Question/Description	*Variable*	*Proportion/Mean*
In the last 12 months, have you donated to environmental organizations?	DONATE • Yes = 1 • No = 0	19.68
Fair trade products are ones that are produced in accordance with social and environmental standards. They are labeled as "fair trade" products. In the last 12 months, have you intentionally purchased fair trade products?	FAIR • Yes = 1 • No = 0	22.17
In the last 12 months, have you personally worked with others in your local community to solve an environmental problem?	COMMUNITY • Yes = 1 • No = 0	9.57
Does your household have an insulated water heater?	HEATER • Yes = 1 • No = 0	68.77
Do you have money invested in a socially responsible fund?	FUND • Yes = 1 • No = 0	23.06
In the last 12 months, have you personally volunteered for an environmental project?	VOLUNTEER • Yes = 1 • No = 0	9.76
In the last 12 months, how often have you personally recycled cardboard packaging or paper?	RECYCLE • Almost daily = 1 • Once or twice a week or less often = 0	46.48
Life Satisfaction, 1 to 10	SATISFACTION	7.24
Controls		
= 1 if respondent is female	FEMALE	56.17
Age	AGE	51.91
= if household annual income above $35,000	INCOME	78.61
Educational Level, 4 to 14 (4 = 7th or 8th grade, 14 = professional or doctorate)	EDUCATION	10.84
= 1 if respondent is married	MARRIED	64.91
Household size	HH_SIZE	2.63
= 1 if respondent is a homeowner	HOMEOWN	83.17
= 1 if respondent is employed or self-employed	EMPLOYED	63.77
= 1 if the individual strongly agrees or agrees that it is "difficult for somebody like me to do much about the environment"	FATALIST	55.96
= 1 if individual believes it is very likely or likely to that climate change will affect him or her personally in the future	PERSONAL	60.05
Four to 40 index, higher values mean respondent states to be more civic-minded about cheating on taxes, riding public transportation without paying the fare, downloading copyrighted music or movies without permission, and buying stolen goods	CIVIC	35.51
= 1 if respondent answers "Yes, somewhat" to "Would you describe yourself as an environmentalist?"	GREEN_SOME	47.83
= 1 if respondent answers "Yes, definitely" to "Would you describe yourself as an environmentalist?"	GREEN_DEF	7.35
= 1 if respondent answers "Yes" to "Does your local community have a recycling program?"	REC_CENTER	81.43

Proportions of dependent variables using largest estimation sample; statistics of controls for full sample; not using sampling weights

Table 2: Probit Base Models (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	DONATE	FAIR TRADE	FUND	COMMUNITY	VOLUNTEER	RECYCLE	HEATER
FEMALE	0.008	0.039*	0.021	-0.032**	-0.014	0.044	-0.058**
	(0.019)	(0.020)	(0.025)	(0.013)	(0.013)	(0.030)	(0.027)
AGE	-0.006*	-0.006	-0.002	0.004	0.000	-0.006	-0.004
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.006)	(0.005)
AGE*AGE	0.000**	0.000	0.000	-0.000*	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MINORITY	-0.025	-0.005	0.014	0.014	0.020	-0.109***	-0.005
	(0.024)	(0.026)	(0.037)	(0.019)	(0.020)	(0.041)	(0.036)
INCOME	-0.003	0.092***	0.064*	-0.043*	-0.016	0.035	0.021
	(0.027)	(0.023)	(0.035)	(0.022)	(0.020)	(0.045)	(0.037)
EDUCATION	0.011*	0.014**	0.011	0.009***	0.014***	-0.001	-0.004
	(0.006)	(0.006)	(0.008)	(0.003)	(0.003)	(0.009)	(0.008)
MARRIED	0.004	-0.003	0.043	-0.020	-0.021	0.033	0.034
	(0.021)	(0.024)	(0.031)	(0.018)	(0.017)	(0.040)	(0.034)
HH_SIZE	-0.008	-0.022***	-0.028**	0.003	0.003	0.023*	0.014
	(0.008)	(0.008)	(0.012)	(0.005)	(0.005)	(0.012)	(0.011)
HOMEOWN	0.052**	0.029	0.050	0.017	0.032**	0.091*	0.109***
	(0.024)	(0.028)	(0.043)	(0.016)	(0.015)	(0.047)	(0.041)
EMPLOYED	-0.028	-0.020	-0.020	-0.014	0.005	-0.014	-0.007
	(0.022)	(0.023)	(0.030)	(0.016)	(0.016)	(0.037)	(0.033)
FATALIST	-0.063***	-0.048**	-0.039	-0.028**	-0.013	-0.118***	0.014
	(0.020)	(0.021)	(0.026)	(0.012)	(0.012)	(0.032)	(0.029)
PERSONAL	0.091***	0.074***	0.065**	0.014	0.022	0.016	0.006
	(0.019)	(0.020)	(0.025)	(0.014)	(0.014)	(0.033)	(0.029)
CIVIC	-0.001	-0.001	0.000	0.001	0.000	0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
GREEN_SOME	0.121***	0.097***	0.047*	0.046***	0.052***	0.176***	0.018
	(0.022)	(0.021)	(0.028)	(0.015)	(0.015)	(0.032)	(0.029)
GREEN_DEF	0.337***	0.364***	0.051	0.149***	0.149***	0.240***	-0.040
	(0.059)	(0.056)	(0.052)	(0.043)	(0.045)	(0.061)	(0.057)
REC_CENTER	.	.	.	.	.	0.284***	.
						(0.037)	
Observations	2423	2413	1886	2425	2417	2200	2423

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the models use sampling weights and include eight regional dummy variables

Table 3: Marginal Effects of Probit Models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DONATE	FAIR TRADE	FUND	COMMUNITY	VOLUNTEER	RECYCLE	HEATER
Coworkers							
Strong connections, medium green talk, high green help	0.051	0.076**	0.115***	0.046**	0.021	0.034	0.064
	(0.031)	(0.035)	(0.043)	(0.019)	(0.025)	(0.053)	(0.051)
Medium connections, high green talk, medium green help	0.081*	0.070	-0.019	0.040	-0.017	-0.014	0.166**
	(0.045)	(0.048)	(0.066)	(0.029)	(0.036)	(0.082)	(0.071)
Neighbors							
Strong connections, medium green talk, high green help	0.015	-0.059*	-0.005	0.038**	0.050*	0.085*	0.007
	(0.028)	(0.030)	(0.041)	(0.017)	(0.027)	(0.050)	(0.044)
Medium connections, high green talk, medium green help	0.064	-0.048	0.093	0.096***	0.109***	-0.015	0.114*
	(0.041)	(0.044)	(0.060)	(0.026)	(0.030)	(0.079)	(0.062)
Family							
Strong connections, low green talk and green help	0.031	0.100*	0.079	0.011	-0.014	-0.063	-0.095
	(0.046)	(0.061)	(0.073)	(0.030)	(0.045)	(0.079)	(0.067)
Strong connections, high green talk and green help	0.167***	0.141**	0.137*	0.072**	0.077*	0.154*	-0.059
	(0.049)	(0.062)	(0.073)	(0.032)	(0.042)	(0.089)	(0.074)
Weak connection, medium green talk and green help	0.145***	0.158**	0.213***	0.045	0.044	0.101	-0.100
	(0.050)	(0.067)	(0.081)	(0.032)	(0.043)	(0.095)	(0.084)
Observations	1486	1478	1198	1488	1485	1371	1421

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The models include controls in Table 2 and regional dummies

Table 4: Marginal Effects of Probit Models for Sub-Sample of Non-Environmentalists

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	DONATE	FAIR TRADE	FUND	COMMUNITY	VOLUNTEER	RECYCLE	HEATER
Coworkers							
Strong connections, medium green talk, high green help	0.013	0.085**	0.122**	0.005	-0.049	0.050	0.129*
	(0.023)	(0.034)	(0.051)	(0.018)	(0.031)	(0.070)	(0.067)
Medium connections, high green talk, medium green help	0.020	-0.130*	-0.101	0.039	-0.030	-0.139	0.230*
	(0.034)	(0.068)	(0.100)	(0.034)	(0.054)	(0.143)	(0.127)
Neighbors							
Strong connections, medium green talk, high green help	-0.018	-0.006	0.067	0.016	0.064**	0.106	0.032
	(0.019)	(0.030)	(0.053)	(0.015)	(0.027)	(0.068)	(0.062)
Medium connections, high green talk, medium green help	0.046	0.051	0.295***	0.092***	0.094**	0.099	0.004
	(0.029)	(0.051)	(0.078)	(0.030)	(0.041)	(0.126)	(0.100)
Family							
Strong connections, low green talk and green help	0.017	0.131**	0.091	-0.006	-0.033	0.006	-0.089
	(0.030)	(0.053)	(0.067)	(0.027)	(0.038)	(0.089)	(0.084)
Strong connections, high green talk and green help	0.096***	0.157***	0.125	0.026	0.034	0.140	-0.128
	(0.037)	(0.060)	(0.089)	(0.027)	(0.043)	(0.121)	(0.103)
Weak connection, medium green talk and green help	0.054	0.165**	0.256***	-0.008	-0.050	-0.008	-0.160
	(0.038)	(0.066)	(0.089)	(0.034)	(0.052)	(0.124)	(0.121)
Observations	692	688	555	596	595	607	659

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the models include controls in Table 2 and regional dummies

Table 5: OLS Model for SATISFACTION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coworkers							
Strong connections, medium green talk, high green help	0.790***				0.831***	0.657***	0.703***
	(0.180)				(0.183)	(0.184)	(0.187)
Medium connections, high green talk, medium green help	0.023				0.089	0.091	0.169
	(0.271)				(0.289)	(0.293)	(0.308)
Neighbors							
Strong connections, medium green talk, high green help		0.770***		0.755***		0.502***	0.482***
		(0.138)		(0.140)		(0.173)	(0.177)
Medium connections, high green talk, medium green help		-0.120		-0.105		-0.408	-0.426
		(0.240)		(0.243)		(0.312)	(0.315)
Family							
Strong connections, low green talk and green help			0.156	0.152	0.059		-0.024
			(0.254)	(0.264)	(0.310)		(0.321)
Strong connections, high green talk and green help			0.200	0.063	-0.038		-0.097
			(0.250)	(0.260)	(0.325)		(0.333)
Weak connection, medium green talk and green help			-0.117	-0.188	-0.246		-0.346
			(0.304)	(0.314)	(0.376)		(0.385)
Observations	1624	2230	2262	2126	1556	1554	1487

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The models include controls in Table 2 and regional dummies

Appendix

Latent Cluster Models: Data and Results

Table A1: Indicators of Family Networks (N = 2,528)

Question	Indicator	Frequency
Ties		
How many of your relatives live within an hour's drive of your home?	Many Family	
• Many or Some	Many Family = 1	57.69
• A few or None	Many Family = 0	42.31
How often do you see any of these relatives?	Frequent Family	
• every day or almost every day or once a week	Frequent Family = 3	27.65
• almost every week or once or twice a month	Frequent Family = 2	40.08
• a few times a year or less often	Frequent Family = 1	32.27
Any of three closest friends is a family member (spouse/partner or other relative)	Friend Family = 1	58.81
Pro-Environment Norms		
Please tell us how many of the following people [Family members] you think do things to help the environment	Help Family	
• Most of them	Help Family = 1	17.45
• Some of them, Few of them, None of them, or Don't know	Help Family = 0	82.55
How often do you discuss with Family members ➢ ways to conserve gas, energy, and water ➢ environmental problems such as water pollution and air pollution ➢ ways to slow down global warming	Talk Family	
• All topics Several times a week, Once or twice a week, or A few times per month	Talk Family = 3	15.87
• Two of the topics Several times a week, Once or twice a week, or A few times per month	Talk Family = 2	18.57
• One of the topics Several times a week, Once or twice a week, or A few times per month	Talk Family = 1	24.36
• None of the topics Several times a week, Once or twice a week, or A few times per month	Talk Family = 0	41.20

Table A2: Indicators of Neighbor Networks (N = 2,504)

Question	Indicator	Frequency
Ties		
How many neighbors do you know and talk to regularly?	Many Neighbor	
• Many or Some	Many Neighbor = 1	35.80
• A few or None	Many Neighbor = 0	64.20
To what extent do [Neighbors] provide you with a sense of community or feeling of belonging?	Belong Neighbor	
• A lot	Belong Neighbor = 1	20.85
• Some or A little or Not at all	Belong Neighbor = 0	79.15
Generally speaking, how much do you trust: Neighbors	Trust Neighbor	
• A lot	Trust Neighbor = 1	37.29
• Some or Only a little or Not at all	Trust Neighbor = 0	62.71
Any of three closest friends is a neighbor	Friend Neighbor = 1	15.68
Pro-Environment Norms		
Please tell us how many of the following people [Neighbors] you think do things to help the environment	Help Neighbor	
• Most of them	Help Neighbor = 1	7.27
• Some of them, Few of them, None of them, or Don’t know	Help Neighbor = 0	92.73
How often do you discuss with Neighbors ➢ ways to conserve gas, energy, and water ➢ environmental problems such as water pollution and air pollution ➢ ways to slow down global warming	Talk Neighbor	
• All topics Several times a week, Once or twice a week, or A few times per month	Talk Neighbor = 3	5.15
• Two of the topics Several times a week, Once or twice a week, or A few times per month	Talk Neighbor = 2	7.31
• One of the topics Several times a week, Once or twice a week, or A few times per month	Talk Neighbor = 1	10.99
• None of the topics Several times a week, Once or twice a week, or A few times per month	Talk Neighbor = 0	76.55

Table A3: Indicators of Coworker Networks (N = 1,827)

Question	Indicator	Frequency
Ties		
To what extent do [People at work] provide you with a sense of community or feeling of belonging?	Belong Work	
• A lot	Belong Work = 1	27.41
• Some or A little or Not at all	Belong Work = 0	72.59
Generally speaking, how much do you trust: People at work	Trust Work	
• A lot	Trust Work = 1	28.61
• Some or Only a little or Not at all	Trust Work = 0	71.39
Any of three closest friends is a coworker	Friend Work = 1	25.37
Pro-Environment Norms		
Please tell us how many of the following people [People at work] you think do things to help the environment	Help Work	
• Most of them	Help Work = 1	8.15
• Some of them, Few of them, None of them, or Don't know	Help Work = 0	91.85
How often do you discuss with People at work ➢ ways to conserve gas, energy, and water ➢ environmental problems such as water pollution and air pollution ➢ ways to slow down global warming	Talk Work	
• All topics Several times a week, Once or twice a week, or A few times per month	Talk Work = 3	11.27
• Two of the topics Several times a week, Once or twice a week, or A few times per month	Talk Work = 2	11.25
• One of the topics Several times a week, Once or twice a week, or A few times per month	Talk Work = 1	16.97
• None of the topics Several times a week, Once or twice a week, or A few times per month	Talk Work = 0	60.51

Table A4: Latent Cluster Models, Fitness Statistics

Model	Log-Likelihood	BIC	Parameters
Family			
1-Cluster	-10616.0948	21294.8267	8
2-Cluster	-10417.8954	20945.4055	14
3-Cluster	-10349.2221	20855.0368	20
4-Cluster	**-10304.7821**	**20813.1346**	**26**
5-Cluster	-10297.6642	20845.8765	32
Neighbors			
1-Cluster	-8250.5627	16563.6921	8
2-Cluster	-7700.8497	15519.0120	15
3-Cluster	**-7650.9950**	**15474.0484**	**22**
4-Cluster	-7635.1624	15497.1293	29
5-Cluster	-7618.3324	15518.2152	36
Coworkers			
1-Cluster	-5696.1620	11444.8663	7
2-Cluster	-5472.0995	11041.7775	13
3-Cluster	**-5435.5741**	**11013.7631**	**19**
4-Cluster	-5427.3143	11042.2797	25
5-Cluster	-5419.5446	11071.7765	31

Table A5: Conditional Probabilities of Four-Profile Model for Family Indicators

	Profile 1	Profile 2	Profile 3	Profile 4
Profile Size	0.3646	0.3004	0.1860	0.1491
Indicators				
Many Family	0.7691	0.6573	0.2341	0.3724
Mean of Frequent Family	2.4309	2.3567	1.0232	1.1369
Friend Family	0.5835	0.6608	0.6370	0.3921
Help Family	0.0009	0.3858	0.2840	0.0367
Mean of Talk Family	0.6812	1.8214	1.5034	0.1075

Table A6: Conditional Probabilities of Three-Profile Model for Neighbor Indicators

	Profile 1	Profile 2	Profile 3
Profile Size	0.5736	0.2513	0.1752
Indicators			
Many Neighbor	0.1578	0.7089	0.5100
Friend Neighbor	0.0391	0.3019	0.3341
Belong Neighbor	0.0056	0.6108	0.2960
Trust Neighbor	0.2124	0.9809	0.0264
Help Neighbor	0.0154	0.1827	0.1024
Mean of Talk Neighbor	0.1042	0.6390	1.0859

Table A7: Conditional Probabilities of Three-Profile Model for Co-worker Indicators

	Profile 1	Profile 2	Profile 3
Profile Size	0.6307	0.1960	0.1732
Indicators			
Friend Work	0.1797	0.4270	0.3267
Belong Work	0.0771	0.8637	0.3240
Trust Work	0.1545	0.8229	0.1579
Help Work	0.0059	0.2602	0.1546
Mean of Talk Work	0.3504	0.7395	2.1176

Table A8: Latent Cluster Models, Summary of Network Characteristics

Coworkers		Profile Size
Profile 1	Weak connections, low green talk, low green help	63.07%
Profile 2	Strong connections, medium green talk, high green help	19.60%
Profile 3	Medium connections, high green talk, medium green help	17.32%
Neighbors		
Profile 1	Weak connections, low green talk, low green help	57.36%
Profile 2	Strong connections, medium green talk, high green help	25.13%
Profile 3	Medium connections, high green talk, medium green help	17.52%
Family		
Profile 1	Strong connections, low green talk and green help	36.46%
Profile 2	Strong connections, high green talk and green help	30.04%
Profile 3	Weak connection, medium green talk and green help	18.60%
Profile 4	Weak connection, low green talk and green help	14.91%