Working Paper Series
Department of Economics
University of Verona

The Diffusion of Information and Behavior in Social Networks: Renewable Energy Technology Adoption in Rural China

Pan He, Marcella Veronesi

WP Number: 6 February 2015

ISSN: 2036-2919 (paper), 2036-4679 (online)

The Diffusion of Information and Behavior in Social Networks: Renewable Energy Technology Adoption in Rural China

Pan He

ETH Zurich

E-mail: pan.he@ifu.baug.ethz.ch

and

Marcella Veronesi*

*Corresponding author:

University of Verona, Department of Economics

Vicolo Campofiore 2, 37129 Verona, Italy.

Phone: +39 45 842 5453

E-mail: marcella.veronesi@univr.it

The Diffusion of Information and Behavior in Social Networks: Renewable Energy Technology Adoption in Rural China

Abstract. Adopting renewable energy technologies has been seen as a promising way to reduce CO_2 emissions and deforestation. This paper investigates how social networks may affect renewable energy technology adoption. We distinguish two channels through which social networks may play a role: (i) the diffusion of information; and (ii) the diffusion of behavior. Most empirical studies fail to quantitatively separate the diffusion of information and behavior in social networks. We conduct a survey on biogas technology adopting in rural China to identify individuals' egocentric information networks. We find that both the diffusion of information and behavior drive farmers' technology adoption. Farmers with larger egocentric information networks and a larger fraction of known adopters are more likely to adopt the biogas technology. In addition, we collect data on several attributes of alters to explore the composition of social networks. We find heterogeneous social network effects across different types of alters. Alters who have close relationships with egos such as friends and relatives or that are trusted by egos affect egos' adoption through the diffusion of information, while less trusted alters such as government officials affect egos' adoption through their adoption behavior.

Keywords: Social networks, renewable energy, technology adoption, information diffusion, behavior diffusion, biogas, China

JEL Codes: D83, D85, Q55

1. Introduction

Renewable energy sources can substitute traditional energy materials such as firewood and coal. Therefore, adopting renewable energy technology may contribute to addressing several problems such as CO_2 emissions and deforestation (Panwar et al., 2011). In this study, we investigate how social networks may affect renewable energy technology adoption.

Social networks affect various economic behaviors and outcomes such as job search (Wahba and Zenou, 2005), school performance (Calvó-Armengol et al., 2009), political participation (McClurg, 2003), farm management (Di Falco and Bulte, 2013), and spread of disease (Eubank et al., 2004). In general, there are two possible channels through which social networks may affect technology adoption: the diffusion of information and the diffusion of behavior (Rogers, 1995; Conley and Udry, 2001; Jackson and Yariv, 2005; Jackson and Yariv, 2007; Kremer and Miguel, 2007; Jackson, 2008). The information about a new technology (e.g., the existence and benefits of the new technology, and how to use the new technology) may diffuse through social networks. Obtaining more information makes individuals more likely to be aware of the technology and improves their knowledge of it, which could affect their adoption of the technology (Conley and Udry, 2001; Jackson and Yariv, 2005; Conley and Udry, 2010).[1]

In addition to receiving information, individuals may be affected by the adoption of the technology in their social networks. Bursztyn et al. (2014) show that people imitate others' adoption because (i) people see others' adoption (or intentions to adopt) as an indicator of high quality of the technology (product); and (ii) the possession of the technology (product) by others may increase an individual's utility from possessing the product.

[1] In most cases, better knowledge increases the probability of adoption. However, as shown in Kremer and Miguel (2007), it may have a negative effect if individuals overestimate the benefits of the technology at the beginning and then figure out the real benefits after obtaining information through their social networks.

However, most empirical studies fail to quantitatively separate the diffusion of information and behavior in social networks. The adoption rate or the number of adopters in social networks is usually used in existing studies to investigate social network effects (Isham, 2002; Bandiera and Rasul, 2006; Kremer and Miguel, 2007). These studies assume people receive information only from every adopter in their social networks and are affected by every adopter's adoption as well. Therefore, the estimated social network effects are aggregate effects. It is not possible to know whether social network effects are driven by the diffusion of information, or the diffusion of behavior, or both. In this paper, we aim to fill in this gap by using biogas technology adoption in rural China as a case study. Biogas is a renewable energy source that can substitute traditional energy materials such as firewood (Panwar et al., 2011). The Chinese government started a subsidy program in rural areas in 2003 aiming to encourage farmers to adopt biogas. However, the adoption rate of biogas technology is still low (about 40%) until 2013 (MOA, 2014).

We implement the following empirical strategy to identify what channel drives the social network effects on adoption. First, we follow Conley and Udry (2010) to identify farmers' egocentric information networks by directly asking them the question "who are the persons giving you some information about the biogas program?". In egocentric social networks, the individual of interest is defined as "ego" and the people connected to the ego are defined as "alters". In our case, alters are people giving egos some information about the biogas program. Then, we further ask egos whether each alter in their information networks has adopted or has intentions to adopt the biogas technology. We examine whether egos are more likely to adopt the biogas technology because of the diffusion of information, that a larger network size, or because of the diffusion of behavior, that is a larger fraction of adopters known to egos.

Our empirical strategy builds on two recent studies that have shed light on the mechanism of social networks. The first study investigates the diffusion of participation in a microfinance program (Banerjee et al., 2013). They find that choosing different persons to spread the information about the program leads to different village-level participation rates. Results show that the difference is due to the diffusion of information rather than the diffusion of behavior. Participants are more likely to pass on information to others than nonparticipants. However, after being informed, a farmer's participation is not affected by the fraction of participants in his information network. The second study is conducted by Cai et al. (2014), who examine farmers' purchase decisions on weather insurance. Similarly, they find that social network effects are driven by the diffusion of information rather than the diffusion of behavior. However, a following-up survey shows that more than 90% of farmers did not know their friends' purchase decisions. This might explain why farmers' purchase behaviors do not diffuse in the social networks. In our case instead, we can take advantage of the fact that egos can observe whether alters have adopted the technology: a household needs to build a biogas pool and alter the house to adopt biogas.[2]

This paper contributes to the literature in several ways. First, we identify egocentric social networks of each individual instead of using the average behavior in reference groups (e.g., villages) to proxy for individual-level social networks as done in many studies (Foster and Rosenzweig, 1995; Pomp and Burger, 1995; Isham, 2002; Munshi, 2004). Manski (1993) points out that the correlation between a person's behavior and the average behavior in a reference group may be confounded by the fact that a person' behavior may be affected by other group members' behaviors, but at the same time individuals in the same group have similar

[2] In our case, farmers know the biogas technology adoption status for 89% of all alters.

characteristics or face the same environment (e.g., students in the same school have similar grades because they have the same teacher).

Second, we directly elicit individuals' full information networks inside and outside the village. Most studies use other types of social networks (e.g., friendship networks) with geographical boundaries (e.g., inside the village) to proxy for information networks. However, individuals may receive information from outside or only from a small number of people inside the defined social networks (Conley and Udry, 2001; Van den Broeck and Dercon, 2011).

Third, we contribute to the literature on renewable energy technology adoption by incorporating the analysis of social networks. The role of social networks on renewable energy technology adoption is mostly ignored. One exception is the study conducted by McEachern and Hanson (2008). They collect data on the whole social network of one village and find that people who receive a larger number of knowledge-leader nominations from social network members adopt the solar photovoltaic technology earlier. Their study misses variation at the village level being focused on only one village, and does not analyze the mechanism through which social network effects work.

Last but not least, we collect data on several attributes of alters which allows us to explore the composition of social networks. We find heterogeneous social network effects across different types of alters. Alters who have close relationships with egos such as friends, are trusted by egos, or live outside egos' village affect egos' adoption by the diffusion of information, while alters such as government official affect egos' adoption through their adoption behavior.

In addition, we find that both the diffusion of information and the diffusion of behavior drive the social network effects on biogas technology adoption. Farmers who have a larger number of alters in their egocentric information networks and a larger fraction of known adopters are more likely to adopt the biogas technology. To illustrate, one more alter in the information networks is associated with a 5% increase in the probability of adoption, which is equivalent to the effect on adoption of increasing the household income by 50%.

Our results are robust to alternative specifications, sample restrictions, and to the inclusion of different explanatory variables. We also implemented a Generalised Sensitivity Analysis (see Imbens, 2003 and Harada, 2013) to assess the extent of potential omitted variable bias. The analysis shows that our results are not sensitive to unobservable heterogeneity, and therefore they are robust to endogeneity concerns.

The paper is organized as follows. Section 2 describes the background for the Chinese biogas program. Section 3 presents the theoretical framework. Section 4 describes the data. Section 5 presents the results on social network effects on farmers' biogas technology adoption. Section 6 performs some robustness checks on our main results. Section 7 concludes.

2. Background

In rural households, biogas is usually produced in a biogas pool of 6-8 m^3 through the methane fermentation process from organic waste (CRESP, 2008; Weiland, 2010). Using biogas may contribute to reducing CO_2 emissions, reducing air pollution, protecting forest lands, and saving time and costs by substituting for traditional energy materials and producing green fertilizers as by-products (Katuwal and Bohara, 2009; Zheng et al., 2010; Panwar et al., 2011).

Aiming to promote the adoption of biogas in rural areas, the central Chinese government launched a subsidy biogas program in 2003. The biogas program is advertised by government officials in each village. Those government officials are villagers as well so they are also eligible to apply to the program. If farmers want to participate in the biogas program, they need to submit an application to village government officials. Then the application is sent to county government officials, who will decide whether to approve it based on the program budget. Participants will receive subsidies to build biogas pools and alter the toilet, the pigsty, and the kitchen, which costs approximately ¥3000. [3] In the north-western and north-eastern areas, the amount of subsidies is ¥1200; in the south-western area the amount is ¥1000; and in other areas the amount is ¥800. It is economically attractive to adopt the biogas technology due to an estimated annual benefit of ¥4500 (MOA, 2007). However, after ten years, the adoption rate of the biogas technology among suitable households is still low, which is about 40% in 2013 (MOA, 2014).

3. Theoretical Framework

A social network is defined as a set of actors and connections (called "ties") between pairs of actors (Wasserman and Faust, 1994). Actors could be persons, organizations, countries, or any units of interest. There are many types of ties such as individual evaluation of one actor by another (e.g., friendship), and the transfer of resources (e.g., receiving information). Egocentric social networks and whole social networks are two types of social networks that are widely investigated (Furht, 2010). An egocentric social network is a social network surrounding one particular actor (called "ego"). It consists of one ego and several actors (called "alters") that have ties with the ego. A whole social network refers to all actors (called "nodes") and ties among them in a bounded community. It is a combination of all community members' egocentric social networks.

Banerjee et al. (2013) have developed a model on the diffusion of a new technology (product) in whole social networks. As shown in Figure 1, in their model, in the initial period 1, only a small number of nodes receive information about the technology. After being informed, they make decisions on adoption. We use the black dots to represent adopters, and use the gray dots to represent non-adopters. Period 1 ends. Period 2 starts, informed nodes begin to spread

[3] One U.S. Dollar ≈ Six Chinese Yuan

information. They pass on information to other nodes that have ties with them (indicated by the dashed lines in the figure). Compared with non-adopters, adopters are more likely to spread the information. The new informed nodes then decide whether or not to adopt the technology. Period 2 ends. Period 3 starts, all informed nodes (that is, nodes that have received information in previous periods) begin to pass on information to uninformed nodes that have ties with them. Then new informed nodes make their decisions after being informed, and start to spread the information in the next period. After a certain number of rounds, all nodes are informed and the diffusion process stops.

[Figure 1 about here]

In the initial period, nodes make their decisions independently since no one has known or adopted the new technology at that time. However, in later periods, nodes' decisions are affected by the fraction of adopters among information providers. Let p_{it} denote the probability of adoption by node i who is newly informed in period t, let F_{it} denote the fraction of adopters among nodes that have provided node i with information in period t, and let X_i denote a vector of controls. Then p_i is given by

$$p_{it} = P(participation|X_i, F_{it}) = f(X_i'\beta + \delta F_{it}) \quad (1)$$

where $f(z)$ is either a logistic or standard normal distribution function.

In their model, Banerjee et al. (2013) assume that one node's adoption status is fully revealed to other nodes. However, one's adoption may be difficult to be observed, and thus might have no effect on other individuals (Cai et al., 2014). Second, Banerjee et al. (2013) assume that people make decisions immediately after being informed, and do not change their decisions in later periods. This implies that if a person decides not to adopt a new technology in one period, she will not adopt the technology also in the next periods, even if she receive more information about the technology and observes that more and more people in her information networks decide to adopt the technology in later periods. This assumption may not hold in reality: individuals may not take their decisions immediately after the awareness of a new technology. In addition, the diffusion of information not only makes people aware of the technology, but also makes them acquire knowledge of the technology, which may also affects their adoption (Conley and Udry, 2001; Conley and Udry, 2010). In the model proposed by Jackson and Yariv (2005), in addition to the fraction of adopters, also the number of adopters is relevant because people who have more adopters in their social networks are more likely to gain better knowledge of the technology. Non-adopters may also spread information and share knowledge of the technology with others.

Therefore, we propose that individuals' decisions on adoption are dynamic, and are affected by the information they receive and by others' adoption to the degree that this adoption is known by nodes. We extend equation (1) to

$$p_{it} = p(participation|X_i, N_{it}, KF_{it}) = f(X_i'\beta + \theta N_{it} + \delta KF_{it}) \tag{2}$$

where N_{it} represents the number of nodes that have provided information to node i by time t; and KF_{it} represents the fraction of known adopters among information providers of node i.

We use this extended model to investigate the diffusion process with regard to the biogas technology at the time t of data collection. Differently from Banerjee et al. (2013), we focus on egocentric social networks of decision-makers in a sub-sample of households in the villages because whole village social networks may not capture the ties linked to nodes outside the village. However, our egocentric social network analysis still follows the overall theoretical framework explained above. In our model, there is a tie between an alter and an ego if the alter provided information about the biogas program to the ego.

4. Data Description

In March and April of 2012, we conducted an anonymous survey in twelve villages of the Hubei Province of China after two pre-tests.[4] We invited the decision-maker of 685 randomly chosen households to the survey with village leaders' help. The response rate was 87%, that is 597 decision-makers participated in the survey.

The adoption status of biogas technology among the surveyed households is diverse. In this paper, we focus on households that have applied to the biogas program but have not built biogas pools yet, households that plan to apply to the biogas program, and households that did not apply and do no plan to apply to the biogas program. We define the first two categories of households as adopters, and the later one as non-adopters. There are 232 households in the sample who have already built the biogas pools. We exclude these households because using biogas might have changed their social networks.[5] The number and types of alters they currently know may not be the alters they knew when they applied to the program. We also exclude 27 households because of missing data on social networks. We obtain a final sample of 338 observations with 197 adopters and 141 non-adopters.

Table 1 summarizes individual and household characteristics of the final sample. On average, respondents are 47 years old and have a middle school education degree which corresponds to nine years of education. The majority of respondents are male (77%). More than half of the respondents worked off-farm for some days in the last year and think that it will be easy to use the biogas technology. The average obtained score of a three-questions knowledge test on using the biogas technology is 2.24 (the maximum score is three, one for each question).[6]

[4] The two pre-test villages were excluded when we randomly chose the survey villages to avoid contamination.
[5] We perform an analysis including this sub-group in the robustness checks. The main results do not change.
[6] The first question is "what is the most used material for biogas? (kitchen waste; pig dung; wood; do not know)". The second question is "Does the biogas pool need to be sealed? (yes; no; do not know). The third question is

The average household has four persons, a land area of 0.66 hectares, an annual household income of ¥24,000, and consumes 546 kilograms of firewood and straws, 262 coal balls, and four tanks of liquefied petroleum gas per year. About half of the households use other renewable energies such as solar power, and raise pigs whose dung is the main material for biogas.

[Table 1 about here]

We identified respondents' egocentric information networks by asking them the question "who are the persons giving you some information about the biogas program?" As we explained to respondents in the survey, the term information refers to any information related to the biogas program and the biogas technology such as how the biogas program is implemented, what biogas is, what the biogas can be used for, what they need to do to use the biogas, or what are the benefits of using the technology. Burt (1984) suggests that usually people lists less than eight alters. In the survey, we set the maximal number of alters to ten, and no respondent named more than seven alters in our data. The questions used to elicit individuals' egocentric information networks are listed in Appendix A. Respondents' information network sizes (the numbers of alters in information networks) vary from one to seven with a mean value of 2.12 and a standard deviation of 1.09. The information network size of adopters (2.27 on average) is significantly larger than that of non-adopters (1.89 on average).

In order to check whether general social networks can capture all the information sources, we also asked respondents the question "From time to time, most persons discuss important matters with other persons. Looking back in the last year –who are the persons with whom you discussed matters important to you?" (Burt et al., 1985). Results show that there are 58% of

"Under suitable conditions, does the biogas pool produce more biogas with lower temperature? (yes; no; do not know)".

respondents for whom their general social networks and their information networks on biogas technology did not overlap, and only 19% of respondents' general social networks contain all persons in information networks. This suggests that using general social networks to proxy for information networks as often done in other studies (Banerjee et al., 2013; Cai et al., 2014) may be not always appropriate.

Importantly, we asked respondents whether each alter had adopted (or had the intention to adopt) the biogas technology. We found a considerable variation in the number of known adopters: 13% of respondents know zero adopters, 38% of respondents know one adopter, 30% of respondents know two adopters, and 19% of respondents know more than two adopters. The average fraction of known adopters in information networks is 0.787. The fraction of known adopters is significantly larger for adopters than for non-adopters.

In addition, we asked respondents about some attributes of each alter in their information networks. This detailed data allow us to explore the composition of social networks and the heterogeneous social network effects of different alters. Table 2 displays the share of alters with different attributes. The biogas program is a governmental program and is advertised to farmers by the village-level government officials. Therefore, government officials become the major information providers (55%). However, egos also receive information from family members (3%), relatives (12%), friends (19%), neighbors (10%), and alters with other relationships such as biogas engineers (7%).

The other attributes of alters elicited include the frequency of communication between the alter and the ego, whether the ego trusts the alter, whether the alter lives inside the village or outside the village, the age, gender, and education of the alter. [7] Alters have diverse communication frequencies with egos. Twenty-eight percent of alters talk to egos at least once

[7] Age is categorized with a range of 10 years in each category. Education level is categorized as none, primary school, middle school, high school, college or beyond.

per day, 37% of alters talk to egos at least once per month, 21% of alters talk to egos at least once per year, and the other alters (4%) talk to egos less frequently. Most alters are trusted by egos (79%). We define egos trusting alters if they are willing to lend money to the alters or they would ask alters to take care of their houses when they go away. About 90% of alters live in the same village of the ego but still some information comes from outside the village, which shows that setting geographical boundaries of social networks as done in many previous studies is not always appropriate. Seventy-four percent of alters have the same gender of the ego, but less than 40% of alters have the same age and education level of the ego.

[Table 2 about here]

5. Empirical Strategy and Results

In this section, we first investigate in section 5.1 whether social networks affect the biogas technology adoption through the diffusion of information and behavior, and then, in section 5.2 we explore the heterogeneity of social network effects.

5.1 Social Network Effects

We investigate social network effects on biogas technology adoption by using a probit model as follows:

$$Y_i^* = \beta_0 + \beta_1 Information_i + \beta_2 Behaviour_i + \beta_3 X_i + \beta_4 V_i + \varepsilon_i \; with \; Y_i = \begin{cases} 1, & Y_i^* > 0 \\ 0, & Y_i^* \leq 0 \end{cases} \quad (3)$$

where Y_i* is a latent variable capturing the utility of ego *i* from the adoption. Ego *i* decides to adopt the biogas technology (Y_i=1) if Y_i*>0, and not to adopt it (Y_i=0) otherwise. $Information_i$ represents ego *i*'s information network size, or in other words, the number of alters in the information network. $Behaviour_i$ represents the fraction of known adopters in ego i's information network.[8] X_i is a vector of ego i's other individual and household characteristics including age, gender, education years, working off farm, household size, land size, household income, using other renewable energies, raising pigs, consumed firewood/straws, coal, and liquefied petroleum gas, perceived ease of use of the technology, score of the biogas technology knowledge test. V_i is a vector of dummy variables to control for village fixed effects, and ϵ_i is the error term capturing unobserved factors.

Table 3 reports the average marginal effects of social networks performing through the diffusion of information and behavior. As shown in columns (1) to (3), the diffusion of information and behavior both have strongly significant effects on biogas technology adoption. In column (4), we control for village fixed effects. The effects are still significant. In column (5), we also control for egos' individual and household characteristics and we find that the social network effects are robust. Having one additional alter in information networks increases the probability of adoption by five percentage points at the 10% significance level. One percentage point increase in the fraction of known adopters is associated with a 0.2% increase in the probability of adoption at the 1% significance level. The social network effects are considerably large. For instance, having one additional alter in information networks increases the probability of adoption by 5% which is equally high as the effect on adoption of increasing the household income by ¥12,500 (half the average household income).

Some individual and household characteristics also significantly affect biogas technology adoption. Young and male farmers are more likely to adopt the biogas technology. Household income has a positive effect. Perceived ease of use and good knowledge of the technology also increases the probability of adoption.

[8] We exclude the adopters if they are family members of the ego because they may live in the same house with the ego and therefore have the same adoption status with the ego.

[Table 3 about here]

5.2 Heterogeneity of Social Network Effects

Alters in information networks differ for several attributes such as relationships with egos, as we described in section 4. Different alters may affect egos' adoption in different ways. We first investigate whether social network effects are different among government officials, family members and relatives, friends, neighbors, and alters having other relationships. We categorize alters based on their relationships with egos and estimate equation (3) using the numbers of alters in each category and the fractions of known adopters in each category instead of using the number of all alters and the fraction of all known adopters as we did in section 5.1. [9] Results are shown in column (1) of Table 4. The numbers of family member and relative alters and friend alters have significant effects on egos' biogas technology adoption. Results of chi-square tests show that the effect of family member and relative alters is not significantly different from the effects of friend alters (chi-square = 0.36, p-value = 0.55), neighbor alters (chi-square = 0.64, p-value = 0.42), and alters having other relationships (chi-square = 2.03, p-value = 0.15), but is significantly different from the effect of government official alters (chi-square = 10.88, p-value = 0.00). Chi-square tests on the equalities of the fractions of known adopters across different relationships generate similar results. The effect of known adopters who are family members and relatives is not significantly different from the effects of known adopter who are friends (chi-square = 0.26, p-value = 0.61), neighbors (chi-square = 0.14, p-value = 0.71), and known adopters having other relationships (chi-square = 0.00, p-value = 0.95), but is significantly

[9] There are 42 alters (6%) exhibiting multiple relationships with egos. Thirty-three alters are government officials and have other relationships. We classify these alters as government officials. Of the remaining alters, five alters are family members or relatives, and have other relationships. We classify them as family members and relatives. The other four alters are both friends and neighbours. We classify them as neighbours.

different from the effect of known adopters who are government officials (chi-square = 4.61, p-value = 0.03).

[Table 4 about here]

Alters differ in the frequency of communication with egos. We classify alters into four categories: (1) alters who talk to egos at least once per day; (2) alters who talk to egos at least once per week; (3) alters who talk to egos at least once per month; and (4) alters who talk to egos less frequently. We estimate how the numbers of alters in each category and the fractions of adopters in each category affect egos' adoption of the biogas technology. Results in column (2) of Table 4 show that the numbers of alters who talk to egos at least once per week is significant while the number of alters in other categories are not significant. However, chi-square tests show that the effect of the number of alters who talk to egos at least once per week is not significantly different with the effects of the numbers of alters who talk to egos at least once per day (chi-square = 0.23, p-value = 0.63), talk at least once per month (chi-square = 1.91, p-value = 0.17), and talk less frequently (chi-square = 0.42, p-value = 0.52). The differences in the effects of the fractions of adopters who talk to egos at least once per week is not significantly different with the effects of the numbers of alters who talk to egos at least once per day (chi-square = 0.72, p-value = 0.40), talk at least once per month (chi-square = 0.08, p-value = 0.78), and talk less frequently (chi-square = 0.52, p-value = 0.47).

In column (3) of Table 4, we separate alters based on whether egos trust them. Results show that the information from trusted alters significantly affects egos' adoption, while the information from untrusted alters has an insignificant effect The difference is significant (chi-square = 3.66, p-value = 0.06). However, the effect of adoption behavior of trusted and untrusted alters is not significantly different (chi-square = 0.50, p-value = 0.48). Both trusted and untrusted alters' adoption significantly affects egos' adoption.

We test whether alters having the same and different characteristics with egos affect egos differently in Table 5. In column (1), we investigate alters living inside and outside the village of egos. Results show that having more information providers outside the village significantly increases egos' probabilities of adoption, while the number of alters inside the village has an insignificant effect. The difference is significant (chi-square = 3.97, p-value = 0.05). However, the difference in the effects of the fractions of known adopters inside and outside the village is not significant (chi-square = 2.17, p-value = 0.14). In column (2), alters are separated based on whether their gender is the same with egos. The effects of the number of alters do not significantly differ between the two types (chi-square = 0.36, p-value = 0.55). Egos are significantly affected by same-gender alters' adoption, while they are not affected by the adoption of alters having different gender with them. This difference is not significant (chi-square = 2.64, p-value = 0.10). In column (3) to (4), we examine alters having the same and different age and education levels, respectively. Alters having the same and different age are insignificantly different either in the diffusion of information (chi-square = 0.00, p-value = 0.99) or in the diffusion of behavior (chi-square = 0.08, p-value = 0.78). Similarly, alters having the same and different education levels are insignificantly different either in the diffusion of information (chi-square = 1.33, p-value = 0.25) or in the diffusion of behavior (chi-square = 0.15, p-value = 0.70).

[Table 5 about here]

The findings on significant heterogeneous social network effects of alters in terms of relationship and trust are particularly interesting. Trusted alters affect egos by passing information to egos. If egos do not trust alters, the information from alters has no effect and egos need to see alters' adoption behavior to be affected. This may explain why government officials affect egos by adopting the technology while non-officials affect egos by providing them information. On average, more than 90% of alters who are family members, relatives, and friends are trusted by egos, while less than 80% of alters who are government officials are trusted, which is significantly smaller at the 1% level. Our results show that farmers are affected by the information provided by their families, friends, and neighbors, but in the case of government officials farmers need to observe that they adopted the technology to confirm that adoption might be indeed a good choice.

In summary, we find that social networks matter for the biogas technology adoption through the diffusion of information and behavior. Heterogeneous social network effects exist across alters with different attributes.

6. Robustness Checks

In this section, we perform several tests on the robustness of our main results presented in Table 3.[10] In column (1) of Table 6, we use a dummy variable equal to one if egos know at least one adopter in information networks and zero otherwise as an alternative measure of the behavior diffusion effect. The behavior diffusion effect is still positive at the 1% significance level. Farmers who know at least one adopter are 20% more likely to adopt the biogas technology than those who know zero adopters.

We use different samples in column (2) and (3) of Table 6. In previous analyses, we defined as adopters households having just applied or planning to apply for the biogas program, and we excluded households using biogas pools for several reasons described in section 3. In this

[10] Appendix B displays the robustness checks of Table 4 and Table 5.

section, we first check whether our results change if we include households that are using biogas pools (column (2) of Table 6), or if we exclude households with biogas pools and households that have just applied for the program (column (3) of Table 6). We find that social network effects are still significant. However, the effect significantly decreases when we include the households that have built biogas pools at the time of the survey.

In addition to social network characteristics and the socio-demographic characteristics previously used in the analysis, in column (4) of Table 6 we also control for respondents' time and risk preferences and personality traits, which might affect adoption and egos' social networks causing biased estimates. We find that the social network effects are still significant after the inclusion of these additional explanatory variables, confirming the robustness of our main results.

Due to missing data, nine observations are dropped when individual and household characteristic are controlled for in column (5) of Table 3. The variables with missing data are land size, household income, consumed firewood/straws, coal, and liquefied petroleum gas, perceived ease of use, and the score of a biogas technology knowledge test. Seven observations have missing data on one variable, two observations have missing data on two variables, and one observation has missing data on three variables. We impute the variables with missing data by first regressing these variables on all other variables and then impute the missing data with predictors. Results are shown in column (5) of Table 6. The behavior effect measured by the fraction of known adopters is still positive and significant at the 1% level. The effect of the number of alters becomes insignificant. However, this effect is not significantly different from that in column (5) of Table 3.

[Table 6 about here]

We control for a considerable number of explanatory variables and village fixed effects in our models to address potential omitted variable bias. However, we cannot completely rule out this bias. There could still be some unobserved factors correlated with social network characteristics and with respondents' decisions to adopt biogas. Therefore, we perform the generalized sensitivity analysis developed by Imbens (2003) and Harada (2012) to investigate how likely it is that our main results presented in Table 3 suffer from omitted variable bias. Figure 2 displays how strongly the omitted variable should be correlated with the outcome (egos' biogas adoption in our case) and with the treatment (the number of alters in the left graph, and the fraction of known adopters in the right graph, respectively) to reduce the treatment effects by half. For each covariate used in the model, the generalized sensitivity analysis calculates how large the bias would be if the covariate was an omitted variable. The covariate with the largest potential omitted variable bias is perceived ease of use as shown in Figure 2. This variable is located far from the curve which suggests that the omitted variables must have correlation coefficients much larger than those of all covariates used in the model to reduce the treatment effect by half, which is unlikely to happen. Therefore, we conclude that the omitted variable bias, even if it exists, it is unlikely to change our main findings.

[Figure 2 about here]

7. Conclusions

This paper investigates how social networks affect technology adoption, and in particular biogas technology adoption in rural China. We find that social networks matter through the diffusion of information and behavior. Farmers who have more alters in their information networks and a larger fraction of known adopters are more likely to adopt the biogas technology. This result differ from Banerjee et al. (2013) and Cai et al. (2014) who do not find that egos are affected by alters' behaviors. Our results highlight the importance of focusing on adopters whose adoption is revealed to egos instead of assuming that egos know every one's adoption status. Researchers need to be cautious when they announce that their results can be extended to the adoption of other technologies because whether egos know other's adoption may depend on the context of the technology.

We also find that alters with different attributes affect egos differently. Egos' adoption is affected by information from more trusted alters such as family members, relatives, and friends. Government officials are less trusted by egos. Therefore, their observed adoption of the technology rather than the provision of information has a significant effect on egos' adoption. Information from outside the village is shown to be quite important. This finding suggests that caution should be used in defining the information networks and setting geographical boundaries.

Our findings have some important policy implications. They support the current practice of relying on government officials to advertise the biogas program. However, information diffusion through government officials is not the most effective way to induce adoption. Farmers are more affected by observing government officials' adopting behavior rather than merely receiving information from them. Information diffusion through alters with closer relationships has larger effects. Therefore, encouraging government officials to adopt, encouraging farmers to pass on information to more people with close relationships, and informing farmers about others' adoption should increase adoption.

This study provides evidence on how social networks affect Chinese farmers' biogas technology adoption. More evidence on other technologies and egos and alters from other countries is needed. Moreover, future research should make more efforts to explore the composition and the formation process of social networks to obtain a better understanding of social network effects on technology adoption.

References

Bandiera, O. and Rasul, I. (2006). Social Networks and Technology Adoption in Northern Mozambique. *The Economic Journal* 116: 869-902.

Banerjee, A., Chandrasekha, A.G., Duflo, E. and Jackson, M.O. (2013). The Diffusion of Microfinance. *Science* 341 (6144): 1236498.

Bursztyn, L., Ederer, F., Ferman, B. and Yuchtman, N. (2014). Understanding Mechanisms Underlying Peer Effects: Evidence from a Field Experiment on Financial Decisions. The American Economic Association Annual Conference, Philadelphia, Pennsylvania, the United State.

Burt, R.S. (1984). Network Items and the General Social Survey. *Social Networks* 6 (4): 293-339.

Burt, R.S., Marsden, P.V. and Rossi, P.H. (1985). A Research Agenda for Survey Network Data.

Cai, J., De Janvry, A. and Sadoulet, E. (2014). Social Networks and the Decision to Insure. The American Economic Association Annual Meeting, Philadelphia, Pennsylvania, the United States.

Calvó-Armengol, A., Patacchini, E. and Zenou, Y. (2009). Peer Effects and Social Networks in Education. *The Review of Economic Studies* 76 (4): 1239-1267.

Conley, T. and Udry, C. (2001). Social Learning Through Networks: The Adoption of New Agricultural Technologies in Ghana. *American Journal of Agricultural Economics*: 668-673.

Conley, T.G. and Udry, C.R. (2010). Learning about A New Technology: Pineapple in Ghana. *The American Economic Review* 100 (1): 35-69.

CRESP (2008). Research Report on "Promotion and Management of Rural Energy Projects". China renewable energy scale-up programme.

Di Falco, S. and Bulte, E. (2013). The Impact of Kinship Networks on the Adoption of Risk-Mitigating Strategies in Ethiopia. *World Development* 43: 100-110.

Eubank, S., Guclu, H., Kumar, V.A., Marathe, M.V., Srinivasan, A., Toroczkai, Z. and Wang, N. (2004). Modelling Disease Outbreaks in Realistic Urban Social Networks. *Nature* 429 (6988): 180-184.

Foster, A.D. and Rosenzweig, M.R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy* 103 (6): 1176-1209.

Furht, B. (Ed.). (2010). *Handbook of Social Network Technologies and Applications*. Springer.

Harada, M. (2012). Generalized Sensitivity Analysis and Application to Quasi-Experiments. Unpublished Work.

Imbens, G.W. (2003). Sensitivity to Exogeneity Assumptions in Program Evaluation. *The American Economic Review* 93 (2): 126-132.

Isham, J. (2002). The Effect of Social Capital on Fertiliser Adoption: Evidence from Rural Tanzania. *Journal of African Economies* 11 (1): 39.

Jackson, M.O. (2008). *Social and Economic Networks*. Princeton: Princeton University Press.

Jackson, M.O. and Yariv, L. (2005). Diffusion on Social Networks. *Economie publique/Public economics* 16: 3-16.

Jackson, M.O. and Yariv, L. (2007). Diffusion of Behavior and Equilibrium Properties in Network Games. *The American Economic Review* 97 (2): 92-98.

Katuwal, H. and Bohara, A.K. (2009). Biogas: A Promising Renewable Technology and Its Impact on Rural Households in Nepal. *Renewable and Sustainable Energy Reviews* 13 (9): 2668-2674.

Kremer, M. and Miguel, E. (2007). The Illusion of Sustainability. *The Quarterly Journal of Economics* 122 (3): 1007-1065.

Manski, C.F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies* 60 (3): 531-542.

McClurg, S.D. (2003). Social Networks and Political Participation: The Role of Social Interaction in Explaining Political Participation. *Political Research Quarterly* 56 (4): 449-464.

McEachern, M. and Hanson, S. (2008). Socio-Geographic Perception in the Diffusion of Innovation: Solar Energy Technology in Sri Lanka. *Energy Policy* 36 (7): 2578-2590.

MOA (2007). Planning of National Rural Biogas Projects (2006–2010). Science and Technology Education Department of Ministry of Agriculture of the People's Republic of China.

MOA (2014). Report on the Work of the Ministry of Agriculture, Ministry of Agriculture of the People's Republic of China, http://www.moa.gov.cn/zwllm/zwdt/201404/t20140403_3839737.htm, April 3rd, 2014.

Munshi, K. (2004). Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution. *Journal of Development Economics* 73 (1): 185-213.

Panwar, N.L., Kaushik, S.C. and Kothari, S. (2011). Role of Renewable Energy Sources in Environmental Protection: A Review. *Renewable and Sustainable Energy Reviews* 15 (3): 1513-1524.

Pomp, M. and Burger, K. (1995). Innovation and Imitation: Adoption of Cocoa by Indonesian Smallholders. *World Development* 23 (3): 423-431.

Rogers, E.M. (1995). *Diffusion of Innovations*. New York: The Free Press.

Van den Broeck, K. and Dercon, S. (2011). Information Flows and Social Externalities in A Tanzanian Banana Growing Village. *The Journal of Development Studies* 47 (2): 231-252.

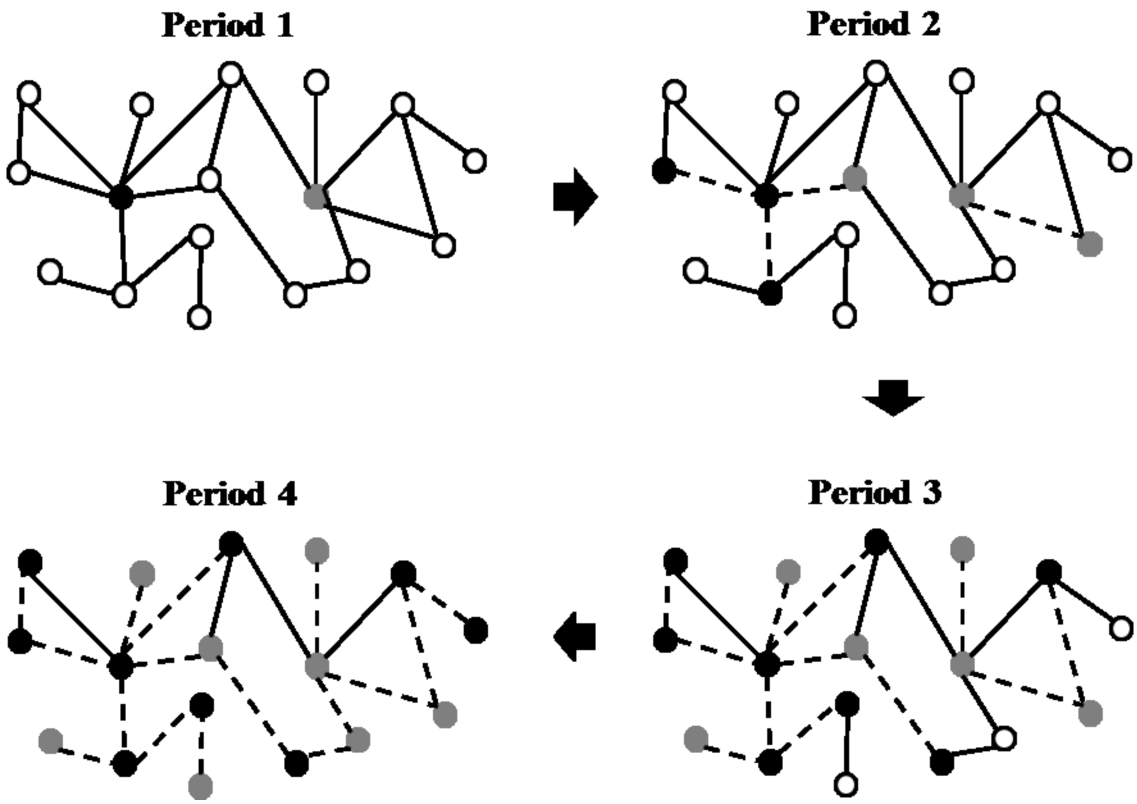
Wahba, J. and Zenou, Y. (2005). Density, Social Networks and Job Search Methods: Theory and Application to Egypt. *Journal of Development Economics* 78 (2): 443-473.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press

Weiland, P. (2010). Biogas Production: Current State and Perspectives. *Applied microbiology and biotechnology* 85 (4): 849-860.

Zheng, Y., Li, Z., Feng, S., Lucas, M., Wu, G., Li, Y., . . . Jiang, G. (2010). Biomass Energy Utilization in Rural Areas May Contribute to Alleviating Energy Crisis and Global Warming: A Case Study in A Typical Agro-Village of Shandong, China. *Renewable and Sustainable Energy Reviews* 14: 3132-3139.

Figure 1. Diffusion of information and behavior in social networks



Note: Adapted from Banerjee et al. (2013). The black dots represent adopters, while the gray dots represent non-adopters. The dashed lines represent the information ties.

Table 1. Summary statistics

	Full sample		Adopters		Non-adopters	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Social network characteristics						
Number of alters in information network	2.118	1.088	2.279	1.220	1.894***	0.826
Fraction of known adopters	0.787	0.358	0.819	0.324	0.742*	0.398
Socio-demographic characteristics						
Age	47.417	8.926	47.020	8.127	47.972	9.940
Gender (1 = male, 0 = female)	0.766	0.424	0.812	0.392	0.702**	0.459
Education years	9.062	2.230	9.396	2.142	8.596***	2.274
Work off farm (1 = yes, 0 = no)	0.524	0.500	0.558	0.498	0.475	0.501
Household size	4.485	1.357	4.548	1.291	4.397	1.444
Land size (hectare)	0.662	0.300	0.660	0.288	0.664	0.317
Household income (¥1000)	24.199	16.189	27.148	17.692	20.071***	12.770
Other renewable energies (1 = yes, 0 = no)	0.521	0.500	0.538	0.500	0.496	0.502
Raising pigs (1 = yes, 0 = no)	0.435	0.496	0.503	0.501	0.340***	0.476
Consumed firewood/straws (100 Kg)	5.462	12.285	4.872	9.798	6.299	15.127
Consumed coal (100 coal balls)	2.616	5.406	2.782	5.681	2.383	5.004
Consumed liquefied petroleum gas (tank)	4.021	2.448	4.365	2.651	3.532***	2.037
Perceived ease of use (1 = yes, 0 = no)	0.611	0.488	0.736	0.442	0.436***	0.498
Score of a biogas technology knowledge test	2.236	0.948	2.436	0.760	1.957***	1.105
Number of observations	338		197		141	

Note: ¥6 ≈ $1. S.D.: standard deviation. *, **, *** Differences between adopter and non-adopters are significant at the 10%, 5%, and 1% levels, respectively.

Table 2. Share of alters with different attributes

Attributes	Percentage
Relationship	
Government officials	55%
Family members	3%
Relatives	12%
Friends	19%
Neighbors	10%
Other relationships	7%
Communication frequency	
day	28%
week	37%
month	21%
year	10%
other	4%
Trust	
Trusted by egos	79%
Untrusted by egos	21%
Location	
Inside the village	90%
Outside the village	10%
Gender	
Same gender with egos	74%
Different gender with egos	26%
Age	
Same age with egos	37%
Different age with egos	63%
Education	
Same education level with egos	33%
Different education levels with egos	77%
Observations	716

Table 3. Marginal social network effects on biogas technology adoption

	(1)	(2)	(3)	(4)	(5)
Number of alters	0.085**		0.092***	0.054*	0.046*
	(0.035)		(0.034)	(0.030)	(0.024)
Fraction of known adopters		0.143**	0.170***	0.194***	0.171***
		(0.056)	(0.063)	(0.074)	(0.061)
Age					-0.006**
					(0.003)
Gender					0.164**
					(0.077)
Education					0.015
					(0.011)
Work off farm					0.039
					(0.041)
Household size					-0.015
					(0.023)
Land					-0.045
					(0.066)
Income					0.004***
					(0.001)
Other energies					-0.054
					(0.038)
Raising pigs					0.043
					(0.057)
Firewood/straw					0.001
					(0.003)
Coal					-0.002
					(0.005)
Liquefied petroleum gas					0.017
					(0.013)
Ease of use					0.252***
					(0.040)
Test score					0.065**
					(0.027)
Village fixed effects	No	No	No	Yes	Yes
Observations	338	338	338	338	329
Log Likelihood	-224.07	-227.75	-221.33	-204.92	-163.79
Pseudo-R2	0.024	0.008	0.036	0.108	0.265

Note: The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table 4. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, and trust

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.003		
	(0.037)		
Family members and relatives	0.168***		
	(0.054)		
Friends	0.119***		
	(0.046)		
Neighbors	0.073		
	(0.074)		
Alters having other relationships	0.079		
	(0.062)		
Fraction of known adopters who are			
Government officials	0.266***		
	(0.058)		
Family members and relatives	-0.022		
	(0.128)		
Friends	0.072		
	(0.148)		
Neighbors	0.058		
	(0.181)		
Alters with other relationships	-0.039		
	(0.287)		
Number of alters who talk to egos			
At least once per day		0.058	
		(0.039)	
At least once per week		0.085**	
		(0.036)	
At least once per month		0.000	
		(0.049)	
Less frequently		0.039	
		(0.072)	
Fraction of known adopters who talk to egos			
At least once per day		0.075	
		(0.115)	
At least once per week		0.191**	
		(0.091)	
At least once per month		0.232*	
		(0.123)	
Less frequently		0.020	
		(0.181)	

Table 4. (continued)

	(1)	(2)	(3)
Number of alters who are			
Trusted			0.066***
			(0.024)
untrusted			-0.036
			(0.051)
Fraction of known adopters who are			
Trusted			0.131*
			(0.070)
untrusted			0.217*
			(0.127)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	329	329	329
Log Likelihood	-158.27	-158.98	-159.37
Pseudo-R^2	0.289	0.286	0.284

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table 5. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, and education

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.033			
	(0.026)			
Outside the village	0.135***			
	(0.048)			
Fraction of known adopters who live				
Inside the village	0.207***			
	(0.061)			
Outside the village	-0.043			
	(0.157)			
Number of alters whose gender is				
The same with egos'		0.056***		
		(0.022)		
Different from egos'		0.017		
		(0.065)		
Fraction of known adopters whose gender is				
The same with egos'		0.230***		
		(0.069)		
Different from egos'		0.032		
		(0.115)		
Number of alters whose age is				
The same with egos'			0.045	
			(0.052)	
Different from egos'			0.046**	
			(0.019)	
Fraction of known adopters whose age is				
The same with egos'			0.175	
			(0.126)	
Different from egos'			0.140***	
			(0.043)	
Number of alters whose education is				
The same with egos'				0.031
				(0.030)
Different from egos'				0.061***
				(0.020)
Fraction of known adopters whose education is				
The same with egos'				0.164*
				(0.090)
Different from egos'				0.194***
				(0.066)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	329	329	322	313
Log Likelihood	-162.01	-159.89	-160.01	-153.52
Pseudo-R^2	0.273	0.282	0.265	0.275

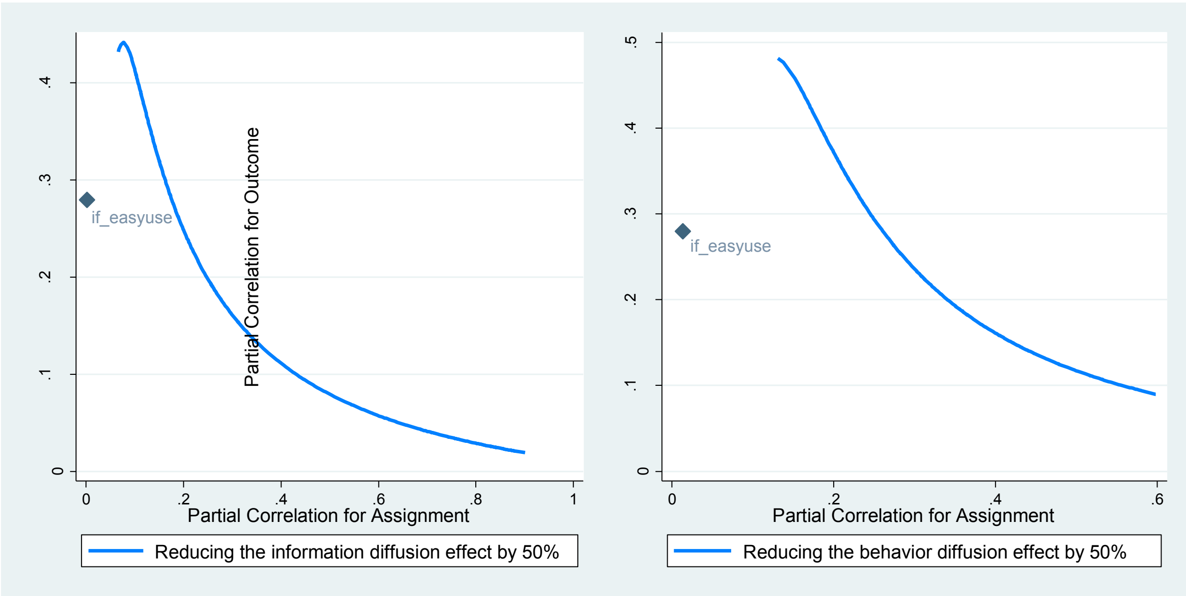
Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table 6. Robustness checks

	(1)	(2)	(3)	(4)	(5)
Information diffusion	0.035	0.034*	0.048*	0.051*	0.040
	(0.023)	(0.020)	(0.026)	(0.029)	(0.027)
Behavior diffusion	0.201***	0.092**	0.213***	0.166***	0.193***
	(0.051)	(0.044)	(0.058)	(0.050)	(0.063)
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	329	537	253	324	338
Log Likelihood	-162.77	-212.59	-128.44	-151.11	-173.14
Pseudo-R2	0.269	0.298	0.265	0.311	0.246

Note: In column (1), the behavior diffusion effect is measured by using a dummy variable equal to one if egos know at least one adopter in information networks and zero otherwise. In column (2), the households with biogas pools are included. In column (3), the households that have applied for the biogas program are excluded. In column (4), we further control for time and risk preferences and personality traits. In column (5), we impute missing data on individual and household characteristics with regression methods. Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Figure 2. Generalized sensitivity analysis



Appendix A. Questionnaire Section on Egocentric Information Networks

Q1: Who are the persons giving you some information about the biogas program?
Q2: What is the relationship of each person with respect to you?
(Family member; Relative; Friend; Neighbor; Government official; Biogas engineer; Other)
Q3: On average, how often do you talk to each person?
(At least once per day; At least once per week; At least once per month; At least once per year; Other)
Q4: If you had to leave the village for a few days, would you be able to ask the person to take care of your house?
(Yes; No)
Q5: If the person borrows money from you, will you lend the money to him/her?
(Yes; No)
Q6: What is the gender of the person?
(Male; Female)
Q7: How old is the person?
(Under 18 years; 18-29 years; 30-39 years; 40-49 years; 50-59 years; 60-69 years; 70 or older; Do not know)
Q8: What is the highest level of education the person has completed?
(None; Primary school; Middle school; High school; College or beyond; Do not know)
Q9: Does the person live in your village?
(Yes; No)
Q11: Has the person submitted, or plan to submit the application for the biogas program?
(Yes; No; Do not know)

Appendix B. Robustness Checks on Heterogeneous Social Network Effects

Table B1. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, trust (using a dummy variable to one if egos know at least one adopter)

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.013		
	(0.034)		
Family members and relatives	0.080		
	(0.058)		
Friends	0.084***		
	(0.031)		
Neighbors	0.102*		
	(0.060)		
Alters having other relationships	0.058		
	(0.038)		
Fraction of known adopters who are			
Government officials	0.164***		
	(0.059)		
Family members and relatives	0.052		
	(0.066)		
Friends	0.050		
	(0.057)		
Neighbors	-0.097		
	(0.083)		
Alters with other relationships	-0.035		
	(0.108)		
Number of alters who talk to egos			
At least once per day		0.024	
		(0.037)	
At least once per week		0.072**	
		(0.035)	
At least once per month		-0.009	
		(0.045)	
Less frequently		-0.027	
		(0.049)	
Fraction of known adopters who talk to egos			
At least once per day		0.023	
		(0.072)	
At least once per week		0.080	
		(0.072)	
At least once per month		0.091	
		(0.070)	
Less frequently		0.071	
		(0.084)	

Table B1. (continued)

	(1)	(2)	(3)
Number of alters who are			
Trusted			0.050*
			(0.026)
untrusted			-0.073
			(0.051)
Fraction of known adopters who are			
Trusted			0.143**
			(0.059)
untrusted			0.278***
			(0.061)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	329	329	329
Log Likelihood	-160.30	-160.84	-155.61
Pseudo-R^2	0.280	0.278	0.301

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B2. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, education (using a dummy variable to one if egos know at least one adopter)

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.021			
	(0.025)			
Outside the village	0.110**			
	(0.048)			
Fraction of known adopters who live				
Inside the village	0.232***			
	(0.057)			
Outside the village	0.010			
	(0.098)			
Number of alters whose gender is				
The same with egos'		0.043**		
		(0.019)		
Different from egos'		-0.027		
		(0.057)		
Fraction of known adopters whose gender is				
The same with egos'		0.214***		
		(0.046)		
Different from egos'		0.099		
		(0.082)		
Number of alters whose age is				
The same with egos'			0.035	
			(0.053)	
Different from egos'			0.012	
			(0.018)	
Fraction of known adopters whose age is				
The same with egos'			0.093	
			(0.094)	
Different from egos'			0.141***	
			(0.043)	
Number of alters whose education is				
The same with egos'				0.009
				(0.037)
Different from egos'				0.042***
				(0.014)
Fraction of known adopters whose education is				
The same with egos'				0.094
				(0.076)
Different from egos'				0.143*
				(0.076)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	329	329	322	313
Log Likelihood	-160.49	-159.11	-159.20	-153.69
Pseudo-R^2	0.279	0.286	0.268	0.274

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B3. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, trust (including households with biogas pools)

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.014		
	(0.027)		
Family members and relatives	0.112***		
	(0.032)		
Friends	0.100***		
	(0.035)		
Neighbors	0.059		
	(0.054)		
Alters having other relationships	0.077**		
	(0.033)		
Fraction of known adopters who are			
Government officials	0.166***		
	(0.037)		
Family members and relatives	-0.023		
	(0.073)		
Friends	-0.003		
	(0.093)		
Neighbors	0.049		
	(0.129)		
Alters with other relationships	-0.006		
	(0.155)		
Number of alters who talk to egos			
At least once per day		0.043	
		(0.028)	
At least once per week		0.078***	
		(0.026)	
At least once per month		-0.016	
		(0.028)	
Less frequently		0.025	
		(0.049)	
Fraction of known adopters who talk to egos			
At least once per day		0.044	
		(0.074)	
At least once per week		0.076	
		(0.086)	
At least once per month		0.163**	
		(0.079)	
Less frequently		0.018	
		(0.105)	
Number of alters who are			
Trusted			0.052**
			(0.022)
untrusted			-0.029
			(0.031)
Fraction of known adopters who are			
Trusted			0.066
			(0.048)
untrusted			0.129
			(0.080)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	537	536	535
Log Likelihood	-205.86	-207.07	-206.83
Pseudo-R^2	0.320	0.315	0.316

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B4. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, education (using the sample including households with biogas pools)

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.026			
	(0.022)			
Outside the village	0.094**			
	(0.037)			
Fraction of known adopters who live				
Inside the village	0.119***			
	(0.044)			
Outside the village	-0.056			
	(0.115)			
Number of alters whose gender is				
The same with egos'		0.037**		
		(0.017)		
Different from egos'		0.032		
		(0.043)		
Fraction of known adopters whose gender is				
The same with egos'		0.147**		
		(0.058)		
Different from egos'		-0.009		
		(0.064)		
Number of alters whose age is				
The same with egos'			0.033	
			(0.032)	
Different from egos'			0.034*	
			(0.019)	
Fraction of known adopters whose age is				
The same with egos'			0.096	
			(0.082)	
Different from egos'			0.080**	
			(0.031)	
Number of alters whose education is				
The same with egos'				0.018
				(0.025)
Different from egos'				0.040**
				(0.017)
Fraction of known adopters whose education is				
The same with egos'				0.077
				(0.075)
Different from egos'				0.111***
				(0.042)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	536	535	523	506
Log Likelihood	-210.80	-208.93	-206.61	-200.23
Pseudo-R^2	0.303	0.309	0.298	0.300

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B5. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, trust (who have not submitted applications)

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.032		
	(0.041)		
Family members and relatives	0.194***		
	(0.071)		
Friends	0.132*		
	(0.074)		
Neighbors	0.141*		
	(0.082)		
Alters having other relationships	0.154***		
	(0.053)		
Fraction of known adopters who are			
Government officials	0.344***		
	(0.072)		
Family members and relatives	0.011		
	(0.193)		
Friends	0.080		
	(0.172)		
Neighbors	0.073		
	(0.203)		
Alters with other relationships	-0.315*		
	(0.175)		
Number of alters who talk to egos			
At least once per day		0.082**	
		(0.035)	
At least once per week		0.072*	
		(0.043)	
At least once per month		0.016	
		(0.064)	
Less frequently		-0.047	
		(0.110)	
Fraction of known adopters who talk to egos			
At least once per day		0.101	
		(0.120)	
At least once per week		0.235**	
		(0.111)	
At least once per month		0.100	
		(0.174)	
Less frequently		0.217	
		(0.206)	
Number of alters who are			
Trusted			0.076***
			(0.025)
untrusted			-0.106
			(0.067)
Fraction of known adopters who are			
Trusted			0.145**
			(0.069)
untrusted			0.375***
			(0.106)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	253	253	253
Log Likelihood	-120.34	-123.59	-121.51
Pseudo-R^2	0.312	0.293	0.305

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B6. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, education (who has not submitted applications)

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.030			
	(0.030)			
Outside the village	0.141***			
	(0.045)			
Fraction of known adopters who live				
Inside the village	0.256***			
	(0.061)			
Outside the village	-0.125			
	(0.209)			
Number of alters whose gender is				
The same with egos'		0.076***		
		(0.022)		
Different from egos'		-0.028		
		(0.063)		
Fraction of known adopters whose gender is				
The same with egos'		0.244***		
		(0.072)		
Different from egos'		0.219**		
		(0.109)		
Number of alters whose age is				
The same with egos'			0.067	
			(0.054)	
Different from egos'			0.039	
			(0.028)	
Fraction of known adopters whose age is				
The same with egos'			0.165	
			(0.158)	
Different from egos'			0.206***	
			(0.042)	
Number of alters whose education is				
The same with egos'				0.065*
				(0.037)
Different from egos'				0.058**
				(0.026)
Fraction of known adopters whose education is				
The same with egos'				0.232**
				(0.093)
Different from egos'				0.286***
				(0.077)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	253	253	247	240
Log Likelihood	-126.22	-125.65	-125.02	-118.74
Pseudo-R^2	0.278	0.281	0.268	0.284

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B7. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, trust (controlling for time and risk preferences, and personality traits)

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.000		
	(0.042)		
Family members and relatives	0.176***		
	(0.056)		
Friends	0.137***		
	(0.051)		
Neighbors	0.084		
	(0.066)		
Alters having other relationships	0.059		
	(0.060)		
Fraction of known adopters who are			
Government officials	0.273***		
	(0.046)		
Family members and relatives	-0.051		
	(0.110)		
Friends	0.048		
	(0.126)		
Neighbors	-0.001		
	(0.181)		
Alters with other relationships	-0.028		
	(0.261)		
Number of alters who talk to egos			
At least once per day		0.052	
		(0.043)	
At least once per week		0.112***	
		(0.042)	
At least once per month		0.008	
		(0.055)	
Less frequently		0.020	
		(0.067)	
Fraction of known adopters who talk to egos			
At least once per day		0.091	
		(0.118)	
At least once per week		0.159*	
		(0.095)	
At least once per month		0.231**	
		(0.117)	
Less frequently		0.071	
		(0.171)	
Number of alters who are			
Trusted			0.075**
			(0.032)
untrusted			-0.042
			(0.046)
Fraction of known adopters who are			
Trusted			0.116**
			(0.059)
untrusted			0.235*
			(0.120)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	324	324	324
Log Likelihood	-144.10	-145.47	-145.56
Pseudo-R^2	0.343	0.337	0.336

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B8. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, education (controlling for time and risk preferences, and personality traits)

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.037			
	(0.030)			
Outside the village	0.138**			
	(0.061)			
Fraction of known adopters who live				
Inside the village	0.201***			
	(0.046)			
Outside the village	-0.016			
	(0.164)			
Number of alters whose gender is				
The same with egos'		0.065**		
		(0.027)		
Different from egos'		0.006		
		(0.059)		
Fraction of known adopters whose gender is				
The same with egos'		0.215***		
		(0.057)		
Different from egos'		0.057		
		(0.106)		
Number of alters whose age is				
The same with egos'			0.055	
			(0.056)	
Different from egos'			0.043***	
			(0.016)	
Fraction of known adopters whose age is				
The same with egos'			0.153	
			(0.107)	
Different from egos'			0.135***	
			(0.042)	
Number of alters whose education is				
The same with egos'				0.033
				(0.038)
Different from egos'				0.065***
				(0.022)
Fraction of known adopters whose education is				
The same with egos'				0.152**
				(0.076)
Different from egos'				0.193***
				(0.069)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	324	324	317	309
Log Likelihood	-149.43	-147.13	-146.73	-140.05
Pseudo-R^2	0.319	0.329	0.315	0.330

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B9. Heterogeneity of marginal social network effects on biogas technology adoption: relationship, communication frequency, trust (imputing missing data on individual and household characteristics)

	(1)	(2)	(3)
Number of alters who are			
Government officials	-0.007		
	(0.039)		
Family members and relatives	0.163***		
	(0.055)		
Friends	0.112***		
	(0.041)		
Neighbors	0.052		
	(0.080)		
Alters having other relationships	0.077		
	(0.061)		
Fraction of known adopters who are			
Government officials	0.299***		
	(0.056)		
Family members and relatives	-0.018		
	(0.127)		
Friends	0.085		
	(0.139)		
Neighbors	0.094		
	(0.185)		
Alters with other relationships	-0.064		
	(0.293)		
Number of alters who talk to egos			
At least once per day		0.052	
		(0.038)	
At least once per week		0.084**	
		(0.041)	
At least once per month		0.005	
		(0.049)	
Less frequently		0.008	
		(0.056)	
Fraction of known adopters who talk to egos			
At least once per day		0.099	
		(0.133)	
At least once per week		0.212**	
		(0.090)	
At least once per month		0.222*	
		(0.120)	
Less frequently		0.071	
		(0.163)	
Number of alters who are			
Trusted			0.058**
			(0.026)
untrusted			-0.034
			(0.056)
Fraction of known adopters who are			
Trusted			0.166**
			(0.073)
untrusted			0.202
			(0.130)
Village fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Observations	338	338	338
Log Likelihood	-167.49	-167.70	-168.68
Pseudo-R^2	0.271	0.270	0.265

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.

Table B10. Heterogeneity of marginal social network effects on biogas technology adoption: location, gender, age, education (imputing missing data on individual and household characteristics)

	(1)	(2)	(3)	(4)
Number of alters who live				
Inside the village	0.027			
	(0.029)			
Outside the village	0.129**			
	(0.051)			
Fraction of known adopters who live				
Inside the village	0.222***			
	(0.059)			
Outside the village	0.046			
	(0.163)			
Number of alters whose gender is				
The same with egos’		0.058**		
		(0.025)		
Different from egos’		-0.013		
		(0.062)		
Fraction of known adopters whose gender is				
The same with egos’		0.225***		
		(0.074)		
Different from egos’		0.128		
		(0.101)		
Number of alters whose age is				
The same with egos’			0.033	
			(0.056)	
Different from egos’			0.044**	
			(0.018)	
Fraction of known adopters whose age is				
The same with egos’			0.215*	
			(0.119)	
Different from egos’			0.155***	
			(0.051)	
Number of alters whose education is				
The same with egos’				0.026
				(0.031)
Different from egos’				0.053**
				(0.026)
Fraction of known adopters whose education is				
The same with egos’				0.197**
				(0.092)
Different from egos’				0.213***
				(0.062)
Village fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Observations	338	338	331	322
Log Likelihood	-171.57	-170.14	-169.48	-163.17
Pseudo-R^2	0.253	0.259	0.245	0.254

Note: Other controls are the same individual and household characteristics used in Table 3. The average probit marginal effects and standard errors clustered at the village level in parentheses are reported. *, **, *** Significant at the 10%, 5%, and 1% levels, respectively.