The health impacts of a community biogas facility in an informal urban settlement: does training matter?

Abstract

Community biogas facilities are being implemented in many informal urban settlements across Africa, often funded by foreign aid. We measured the public health impacts of a facility in Ethiopia, particularly the effects of training, in the context of extreme poverty. Two waves of panel-data were generated by household surveys (N=200 per wave), informed by participatory focus groups, and a propensity-score matching technique was applied. After controlling for household distance from the facility, training itself generated positive effects on health including use of improved sanitation facilities and self-assessed health. We conclude that training should be considered a key component in biogas development.

Keywords: Training; Biogas; Health; Foreign Aid, Propensity-Score Matching.
Main Text

1. Introduction

Poor sanitation remains a main cause of death in developing countries, and in Ethiopia alone around half a million children under five years die annually from this and related causes, such as lack of clean water. These numbers are higher those registered for the African continent at large, and higher than the global annual rate of infant deaths (WHO, 2015). Notwithstanding significant improvement over the past decades, child mortality in Sub-Saharan African countries remains close to 17 times higher than it is in developed nations (Farr, Nelson, 2014).

Most studies on the public health effects of sanitation projects focus on reducing mortality (Clasen, Schmidt et al. 2007). Although some question their cost-effectiveness (Whittington, Jeuland et al. 2012), there is general agreement that such investments remain key to enhancing public health and raising living standards. Investments in small-scale biogas digesters are generally considered to be particularly worthwhile, also providing a continuous energy supply. Facilities are usually accompanied by training, but this tends to focus only on technical aspects of maintenance, while there is scope to test the role of training as a driver of health outcomes.

We contribute to the scholarly literature by focusing on the role of training as a key component of biogas and sanitation development intervention. The context is an Informal Urban Settlement (IUS) in Ethiopia, characterised by extreme poverty, poor sanitation and exposure to climate-sensitive risks. Here, a biogas facility (funded by foreign aid) was set up in 2013 and training was provided to 45 of the 200 households targeted by the project.
Understanding how training itself might change public health outcomes has important policy implications given that many countries have plans to implement such facilities (Clemens et al., 2018), often funded by foreign aid. This evaluation of a small-scale community project can also contribute to the development of theoretical frameworks which otherwise rely on aggregate data and lack context-specific information.

Poor public health and high rates of childhood mortality in developing countries are often attributable to poor sanitation, lack of clean water and indoor air pollution, and to other characteristics of poverty such as poor nutrition, overcrowding and poor waste management. In turn, poor sanitation, including inappropriate management of waste, and lack of clean water are directly associated with gastro-enteric diseases, including typhoid and parasitic infections, polio and trachoma (Golovaty et al., 2009). Malnutrition, especially in situations of overcrowding, compounds gastro-intestinal infections and contributes to infectious disease transmission. Indoor air pollution from cooking with biomass fuel also has links to respiratory illness, eye infections, diarrhoea, low birth weight, anaemia, and growth stunting (Mishra, Retherford, 2007). Smoke exposure from burning solid biomass, responsible for four to five percent of annual global mortality, is linked to childhood pneumonia, lung cancer, and cataracts (Fullerton, Bruce et al. 2008).

Biogas digesters are normally installed to increase energy supply and to produce freely available bio-fertiliser in low-income communities. They improve standards of living and promote multidimensional development at community-level (Smith, Schroenn Goebel et al. 2014: 359). And, if well-executed they bring added benefits of improved sanitation and health outcomes for low-income households (Hallding, Li et al. 2012). Studies on the health impacts of biogas installations find reductions in paratyphoid, cholera, and dysentery bacteria, while
the use of latrines is also linked with fewer flies and lower rates of trachoma, and gastro-intestinal diseases (Bensah, Mensah et al. 2011). Biogas digesters also lower indoor air pollution by reducing reliance on indoor biomass burning, in turn reducing respiratory and non-respiratory illnesses (Fullerton, Bruce et al. 2008).

But improved facilities need not always translate into better health standards, particularly in the absence of training, awareness or education to stimulate the behavioural change needed for long-lasting development (Billing, Bendahmane et al. 1999). Training is, in fact, often included in development programmes, either as a primary objective or by way of accompanying foreign aid interventions (Wanjala, Muradian 2013). When tested, training has been found to be an important component for biogas investments generally: increasing understanding of their use and the exploitation of the bio-slurry by-product. Training on the use of the bio-slurry improves the handling of animal waste, also with evident health benefits. Lack of training suppresses full exploitation of the benefits of stove replacement programmes, and lowers biogas production, with consequences on pathogens (Jiang, Sommer et al. 2011).

Predominantly however, training has been perceived as a means to building technical and management capacity, and studies have mainly focused on the relationship between training and the use of improved sanitation facilities (Ilahi, Grimard 2000). Many studies are also limited to single health impacts such as diarrhoea (Fewtrell, Kaufmann et al. 2005). Moreover, the bulk of the research on biogas digesters has focused on rural areas, or schools, generally excluding IUSs (Clasen, Schmidt et al. 2007) where impacts can be compounded by crowding (Fenn 2012). It remains in question as to how training activities that support biogas development interventions effect health outcomes in low-income urban communities (Fullerton, Bruce et al. 2008: 849). We address this gap by assessing the impacts of a biogas
development intervention in the context of an IUS, where training on both the use and impacts of the facility, was selectively provided to some of the households. We hypothesise that once other relevant factors are controlled for, training itself improves public health. We further hypothesise that training interacts with access to the biogas facility, such that households residing closer to the biogas facilities enjoy additional, multiplicative positive impacts on health.

2. Materials and Methods

2.1. Context

The biogas facility was installed in Shashemene Ethiopia, a town 250 km South of Addis Ababa, in the West Arsi Province of the Oromia Region. It formed part of a project designed and implemented by a Non-Governmental Organisation (NGO) and funded by Foreign Aid from Malta. The facility included a biogas digester, comprised of four latrines and an adjacent communal kitchen fuelled by the self-produced biogas. A biogas digester is a large tank inside which biogas is produced through the decomposition of organic matter, or biomass. Using animal and human waste, vegetables, leaves, grass, weeds, leftover food scraps as inputs, it employs a process called anaerobic digestion to produce a mixture of carbon dioxide and methane, resembling liquid petroleum gas. This biogas output is used, among other practices, as a fuel in gas cookers for cooking. A further output produced by the biogas digester is the slurry (processed biomass minus the biogas), which is used as organic fertilizer on crops grown close to the project site. Besides four biogas burners, the kitchen was furnished with two fuel-saving wood stoves for cooking traditional bread (enjera). The addition of such stoves is a common characteristic of many biogas systems being implemented in Ethiopia, given that conventional (bio)gas burners do not allow the cooking of enjera, a specific staple food that
requires a larger surface. The intervention also included a water point from the town’s aqueduct supplied with a meter. The facility is owned by the local municipality (also called Katena nr 1), but managed by an ad-hoc local management committee, elected among the members of the community.

The community benefitting from the intervention comprises of 200 households, with approximately 720 individuals who identify themselves as belonging to Katena nr 1, and all of whom had access to the biogas facilities as of October of 2012. The physical boundaries of the IUS are well-defined, by roads, laneways and rivers, and the whole area covers approximately 0.03 km². The use of the bio-gas kitchen appears to be widespread among all households residing in the community, and to have been used as an alternative to the small charcoal burners (traditionally used for cooking within their homes). Distance is likely to be a key determinant in the regular use of the facilities by households.

The project involved training for 45 household heads (or their designate) identified by community leaders and NGO local personnel. Due to budgetary constraints it was not possible to train all the community but selection of households occurred with a view to capturing the diverse socio-demographics of the community. None of the 45 households declined the offer to be trained, nor dropped out or missed any of the three days of training. The training itself was provided during June 2012 (before the biogas digester became operational) by experienced personnel from the local NGO (‘WCDO’) in communal spaces. It covered features and benefits of the biogas installation, key principles of sanitation, public health, and environmental management, by following established protocols developed by the World Health Organization (WHO). Training also included information on the management of the organic slurry produced by the biogas plant.
2.2. Interview design

To test our hypotheses, we first conducted Participatory Rural Appraisals (PRA) with the intent of identifying the relevant health variables, the context-specific determinants. This allowed us to design a suitable questionnaire and to gather data before and after the intervention from the 200 households. PRAs involve eliciting answers in an active, participatory and inclusive manner (Chambers 2008), and have been used increasingly to support quantitative analysis in economic research, by helping to identify context-specific resources and challenges, while avoiding cherry-picking of issues (Casey, Glennerster et al. 2012).

The preparation of the survey interview was also guided by similar studies in developing countries (Mamo, Sjaastad et al. 2007), and by relevant research on sanitation and biogas (Lohri, Rodić et al. 2013). These included questions on the burden of disease such as diarrhoea, eye infections, typhoid, malaria,\(^5\) the management of animal and human waste and self-assessed levels of health. While such measures are an imperfect substitute to objective measures (Krueger, Schkade 2008), they are often considered to be valid and reliable (Kahneman, Deaton 2010). Self-assessed health is commonly used to investigate changes in health status (Doiron, Fiebig et al. 2015). The use of scales (as applied in this research) is considered to help reduce self-reporting biases (Headey, Ecker 2013). It is also reasonable to assume that the bias of self-reporting is equally present among treated and control groups. Indirect effects on health were also measured by eliciting information on behaviour, specifically water deprivation, the use of biogas kitchen and improved sanitation (Banerjee, Deaton et al. 2004). The questions in the interview also attempted to capture data comparable with key national or regional statistics wherever available.
The final survey included questions on household characteristics, public health, including access to and use of sanitation facilities, water and management of environmental resources, frequency and effects of common diseases, employment and assets. To improve accuracy of response and avoid misinterpretation, multiple-choice responses for frequency ranges were used wherever possible, scales were kept similar, and time periods were clearly specified (Tourangeau, Rips et al. 2000). The surveys were translated into the most widely understood local language, Amharic, and piloted (n=10).

2.3. Sample and data
The data were collected through pen-and-paper interviews by four trained university students residing in the settlement. Random checks and further supervision and assistance were provided by the research team throughout the surveying process. The first survey was conducted in September 2012, before the biogas project became operational, and the second in September 2013, following a year of its operation. One year was considered long enough to start detecting changes due to project intervention while minimising any response differences associated with season (Rothman, Thomas 1994). Due to attrition between the two waves of data collection, a total of 31 household members were excluded. This corresponds to eight per cent of the total observations, similar to rates of attrition experienced between survey waves in developing countries, and exhibiting similar characteristics, such as lower income, younger households (Maluccio 2004).

Table 1. Community versus Regional means.
Table 1 compares the survey community results (first wave) with regional means drawn from data collected by the Ethiopian Central Statistical Agency (2011), the World Bank (2013) and the Ethiopian Urban Studies by the University of Bath (2006). Overall, the community is reasonably representative of the West Arsi Province: Household size, ethnicity, religious affiliation, education levels, assets and monthly income and burden of diseases, such as malaria and typhoid, are closely aligned. However, there is a slight difference in dwelling size and weekly employment hours. A lower number percentage of households have been vaccinated against measles compared to the national/regional mean.

Table 2 outlines the key variables with their descriptive statistics, used in the analysis. The choice of the outcome variables to be assessed was pre-informed by both the literature on impact evaluation of similar WASH projects, and by the participatory focus groups with the community and cover physical health levels, diagnosis of typhoid, malaria, days spent sick with diarrhoea, eye infections, and without drinking water. The perception of bad odours in the community is variable that is less frequently considered but is one that is very relevant to the biogas facility. The variables, “training” and “biogas”, are the main explanatory variables of interest where training takes the value of 1 if households received training and 0 otherwise. Biogas proxies the distance of households from the biogas facilities, taking the value of 1 if the facility is close and 0 otherwise. To obtain this variable, households were divided into one of two radii of distance from the biogas: A walking distance of 100 meters from the biogas facilities being close and over 100 meters being far. The geographical characteristics of the community offered a natural cut-off point in a road that intersects the community, suggesting that a binary variable would be a suitable proxy to capture the phenomenon of distance. Discussions with community leaders also confirmed that this distinction is perhaps the only meaningful one in terms of distance. We also examined the distance of households from bio-
gas facilities and divided this into 5 radii of increasing length and examined whether such radii would contribute explanatory power to the estimation. No additional explanatory power was gained. The remaining variables are factors that can affect health directly and indirectly.

Table 2. Key variables in the two waves of survey collection.

2.4. Estimation model

This unique dataset enables us to estimate the impact of training and biogas on health. We assume that health is a function of a vector of household characteristics, \( X_{it} \), (including demographics, socio-economic assets and public health status) and training (\( T_{it} \)), as per Equation 1. In specifying the model, the \( X \) variables were selected with a view to their being exogenous.

\[
Y_{it} = X'_{it}\beta + \delta T_{it} + \alpha B_{it} + \mu_{it} \quad (1)
\]

where

- \( Y_{it} \) is the health outcome of the household \( i \) in period \( t \),
- \( X_{it} \) is a vector of characteristics of household \( i \) in period \( t \)
- \( T_{it} \) is training where \( T_{it} = 1 \) for trained households and \( T_{it} = 0 \) otherwise
- \( B_{it} \) is distance from biogas where \( B_{it} = 1 \) for close households and \( B_{it} = 0 \) otherwise
- \( \mu_{it} \) is the error term

As the training condition was not randomly assigned, estimating the effect on health variables with Ordinary Least Squares (OLS) runs the risk of capturing an effect which is due to unobserved characteristics rather than to the treatment of training. Households that agreed
to take training may systematically differ in some ways from the others in the community. Since the factors that determined treatment could also be determining the selected outcome, this could cause a self-selection bias (Heckman, James, Ichimura et al. 1998). We therefore employ a Propensity-Score Matching (PMS) technique to address any possible initial bias (Rubin 1974). This technique essentially identifies a group of untreated individuals (in this case households) who are similar enough to the treated (trained) group to provide the counterfactual (untreated) data. This then allows the identification of any causal effect due to the treatment. PSM can be applied in a binary treatment scenario, where the treatment indicator $D_i$ equals one if household $i$ receives training and zero if does not receive it. The potential outcomes are subsequently defined as $Y_i(D_i)$ where $N$ represents the total population. The treatment effect for a household $i$ may be formalised as:

$$\tau_i = Y_i(1) - Y_i(0) \quad (2)$$

Only one of the potential outcomes, $Y_i(1)$, is actually observed for each household $i$ that received training. The unobserved or counterfactual outcome, $Y_i(0)$, is not. The (population) average treatment effect is represented by the ‘average treatment effect on the treated’, which can, in turn, be defined as follows:

$$\tau_{ATT} = E(\tau|D=1) = E[Y(1)|D=1] - E[Y(0)|D=1] \quad (3)$$

where

$\tau_{ATT}$ is the average treatment effect on the treated

E is the mean of potential outcome Y

D = 1 representing participation into treatment.
The objective is to estimate \( \tau_{\text{ATT}} \), and find a suitable replacement for the unobserved counterfactual mean \( \mathbb{E}[Y(0)|D=1] \). The comparison group is found by using a model of the probability of participating in the treatment, using observable characteristics, as follows:

\[
P(X) = \Pr[D=1|X] = \mathbb{E}[D|X]; \quad P(X) = F\{h(X)\} \tag{4}
\]

where

- \( P \) is the probability of observing a household with \( D=1 \);
- \( F\{-\} \) is the logistic cumulative distribution; and
- \( X \) represents a vector of pre-treatment features (household size, age, gender, vaccination against measles, religion, number of rooms, and education levels).

This process \textit{matches} trained and non-trained households allowing an Average Treatment Effect on the Treated, \( \tau_{\text{ATT}} \) to be calculated by taking the mean difference in outcomes among the two groups. In order for the PSM to properly construct comparable groups and identify the intervention effect, it needs to satisfy two assumptions, namely \textit{a.} conditional independence and \textit{b.} common support. For conditional independence, participation in the programme must be based only on observable characteristics. For common support treatment observations must have comparison observations ‘in the vicinity’ within the propensity score distribution (Heckman, James J., Ichimura et al. 1997). These assumptions are further explained, and properly tested, below in section 2.5.

The PSM estimator for \( \tau_{\text{ATT}} \) can therefore be formalised as follows:

\[
\tau_{\text{PSM/ATT}} = \mathbb{E}\{\mathbb{E}[Y_i(1)|D_i=1, P(X)] - \mathbb{E}[Y_i(0)|D_i=0, P(X)]\} \tag{5}
\]
where

D is training participation, where D = 1 for trained households and D = 0 otherwise;

P is the probability of observing a household with D=1;

X is a vector of pre-treatment features (including demographics, socio-economic assets and public health status);

E is the mean of potential outcome \( Y_i \)

The PSM estimator is nothing else than the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants. This now enables us to test the hypothesis that training affects health outcomes by examining the differences in key health factors between households who received training and those (similar households) that did not, before and after treatment.

**2.5. Matching procedures and sensitivity analysis**

In our PSM model (Equation 4) the dependent variable is that capturing training. The selection of the variables used to create the logit model, on which the PSM could be calculated, included a range of characteristics that go beyond demographics (Thoemmes, Kim 2011). The inclusion of these factors aims at increasing the robustness of the PSM model, while excluding covariates that may run the risk of creating bias in the estimation of training effects (Rubin, Thomas 1996). At the same time, the estimation model must be parsimonious, with relevant covariates to achieve a rigorous matching (Rubin, Thomas 1996). To this end, the variables included were: i. household size, ii. age, iii. gender of respondent, iv. vaccination against measles, v. religion, vi. number of rooms in the home, and vii. education levels.
The estimation procedure made use of the psmatch2 programme (Leuven, Sianesi 2012) in the STATA© (version 12) statistical software package. To match participants we tested both the Nearest-Neighbour Matching (NNM) and Kernel Based Matching (KBM) algorithms. To improve reliability and robustness of the matching, a trimming procedure corresponding to 0.01 was applied, dropping treatment observations at which the propensity scores density of the control observations is the lowest, (Caliendo, Kopeinig 2008). The trimming procedure does not change the results for the ATTs and their levels of statistical significance, but allow us to improve the robustness of the matching by strengthening the common support assumption. Since estimation of PSM with NNM can run the risk of bad matches if the closest neighbour is distant (Austin 2009), a calliper of 0.3 was applied, where observations (in our case seven) larger than 0.2 of the standard deviation of the logit of the propensity score are dropped. The NNM also included a one-to-many matching with replacement, to improve the variance of the estimators (Smith, Todd 2005), with no weights applied. While time-varying heterogeneity can create bias, we are confident that there were no macroeconomic changes, nor health-related issues, that affected the two groups differently during the program. Both project and control areas had analogous pre-program features, especially in the socio-economic and health spheres. Testing for the presence of heteroscedasticity we find minor changes between unadjusted Standard Errors and Huber-White Standard Errors, with no change in any of the significance levels. The authors have no reason to believe that error terms cluster in other ways.

When testing for the common support assumption, we found good matching in the region of common support on selected statistically significant variables, as also shown by the values reported in Table 3. The ignorability assumption holds if conditional on the observed
covariates, and the selection into the treatment is unrelated to unmeasured variables. We tested the robustness of this assumption providing a formal sensitivity analysis, as shown in Table 3.

Table 3. Household characteristics (trained/not-trained), before/after matching.

Table 3 shows how the sample means of the covariates selected for the matching model changed after the matching procedure took place. The expectation here is that, once households are matched the differences between treated and control households would be lower. This is in fact the case for all the variables selected in our PSM model, as also shown by the columns displaying $p$ and $t$-statistic values. In order to test the distance in marginal distributions of the X-variables, before and after matching (Rosenbaum, Rubin 1983), we used the $ptest$ command in STATA by examining the Standardized Bias (SB), and added a further test of the total percentage reduction in bias. We followed this procedure and found that the post-matching bias ranges from 4.6 to 11.8, as reported in Table 4, which are considered to be sufficient percentage bias thresholds (Caliendo, Kopeinig 2008). Given the possibility of still having unobserved covariates that might bias our estimated training effects, we perform a sensitivity analysis that generates a hypothetical unobserved variable, U, and manipulates its effects on having training, placing a ‘bound’ (also known as ‘Rosenbaum bounds’) for significance levels and confidence intervals across the training effects, assessing how strong the unmeasured variable must be before the training effect is weakened (Alvarado, An 2015). Applying an extension of Rosenbaum bounds, called Mantel–Haenszel bounds, which specifically addresses unobserved heterogeneity (i.e., “hidden bias”) we use two bounding approaches to examine critical level of gamma $\Gamma$, which describes the level at which causal inference of significant training impact start to become questionable, therefore where the conditional independence assumption does not hold. The first ($\Gamma_{mh}$) focuses on binary
variables (Becker, Caliendo 2007), while the second (Γrb) is more suitable for continuous variable (DiPrete, Gangl 2004). This sensitivity analysis incrementally manipulates the odds ratio of having training, gamma (Γ), until the original ATT is no longer statistically significant. That is, we continue to increase the odds of having training attributed to U until we “kill” our observed statistically significant (p < 0.05) ATT from the propensity score model, which we evaluate by examining the corresponding p-value associated with each increase in Γ. Our increments for Γ are in the metric of odds ratios and are 0.05 in size, ranging between 1.00 and 2.00. Results closer to 2 confirm the absence of hidden bias, allowing us to attribute the cause of that change to training, while results that are close to 1 require caution in interpretation. This approach has often been used to test the ignorability assumptions (Becerril, Abdulai 2010). Our results show that critical levels of gamma Γ confirm the absence of hidden bias (Table 5), with the exception of the variable “malaria” where critical levels of Γ are low. For this specific variable the results do not exclude hidden bias.

Table 4. Sensitivity analyses before/after matching for key PSM indicators.

3. Results

Table 5. Impacts of training on health indicators.

Following the matching procedure, it is possible to examine the public health outcomes where training has an effect. The results in Table 5 represent the difference between trained and those not trained (the ATT in Model 5).10 Three sets of results are presented, namely those for all the households (A), those for the groups living close (C) and those living far (F), thereby controlling for the possible effects of distance from the biogas facilities. The results show that, after controlling for proximity to the biogas, the effects of training on health vary in statistical significance and intensity.
A first examination of the 200 households reveals that a number of health parameters appear to be causally and directly affected by training. Respondents who received training reported significantly ($p = 0.05$) higher levels of self-assessed health in the second survey wave, compared to those who did not receive training. The ATT is 0.31, in the context of a scale between 1 and 5, where 1 is “very poor” and 5 is “very good”. Significant differences (between training and untrained groups) also occurred in the use of the new biogas latrine ($p = 0.01$) and in the use of the biogas kitchen ($p = 0.01$) where the ATTs differences were 1.12 and 0.56, respectively, both on a scale between 0 and 4, where 0 was “never” and 4 was “always”. Interestingly, bad odours were perceived as less of a problem among those who undertook training. A significant ($p = 0.05$) difference of -0.39 was observed, where attitude was measured on a scale between 1 to 5, with 1 being “highly disagree” and 5 “highly agree” respectively. Training, it may be argued, should have triggered an increased awareness over the problem of bad odours, therefore potentially prompting a more critical expectation with results going to the opposite direction. We consider that this specific result could present some elements of desirability bias: training might have triggered an aspiration for improvement not necessarily related to a real change in perception of bad odours.

We next examine the relationship between training and health outcomes controlling for the impact of distance from biogas. We find, as hypothesised that training induced more pronounced positive differences for respondents residing close to the biogas. Households that received training experienced significantly ($p = 0.01$) higher levels of self-assessed health, with an ATT of 0.83, on the scale between 1 and 5, where 1 is “very poor” and 5 is “very good”. There was also a significant difference in the number of cases of typhoid diagnosed. Respondents who received training showed a decrease of -0.17 ($p = 0.10$), on a scale between
In this sub-group, attitudes towards bad odours also changed significantly \( (p = 0.01) \) with training. Similarly, training has a significant \( (p = 0.01) \) and positive effect on the use of the new biogas latrine, with an increase of 1.65 for those who received training. Use of the kitchen was also higher among the trained, with a significant \( (p = 0.10) \) difference of 0.67. No significant change can be seen for days sick with diarrhoea, eye infections and periods without water. For households living further than 100 metres from the biogas facilities, there is no direct health outcome that is being causally affected by training and few indirect effects. The only two variables positively affected by training are the use of the new biogas latrine \( (p = 0.05) \), with an increase in the ATT of 0.59, and the use of the new kitchen \( (p = 0.10) \), with a difference of 0.38.

4. Discussion and Conclusions

A plausible concern with the analysis is that the benefits that accrued among households that received the training spilled over to those households which did not. Such transfers of positive effects have been observed in sanitation projects (O'Loughlin, Fentie et al. 2006: 1141). This would suggest that our findings are actually lower bound estimates and that the effects of training, in fact, may be larger and more widespread than those observed. Further research with larger samples could also look into possible changes in health outcomes among specific sub-groups of the population, such as women and youth who generally exhibit lower health standards in IUS.

The results showing a decreased level of typhoid should be interpreted with caution, given that only routine microbiological tests (not measured by this research) can accurately determine if the disease being identified by the respondents is indeed typhoid. However, the
bias in detection of typhoid is no more likely to be present among the treatment and the control groups. Also, while self-assessed variables including physical health are considered to be robust both by the literature and international organizations such as the WHO, perception of odours is arguably more complex (Ehmke, Shogren 2010).

We also acknowledge that a randomised controlled experiment would have facilitated the identification of training effects. This was, however, not a realistic option on the ground. In applying matching methods, we hope to have illustrated the possibility of testing effects in similar scenarios where randomly assigning households into treatments is not feasible. Research applying PSM methods with similar sample size, either contextualised at community level or tested with ad-hoc simulations (Becerril, Abdulai 2010), tend to confirm the validity of such methods, at least in terms of removing the initial selection bias. In the presence of a rich data set, the number of hypotheses being tested, the risk of false discovery becomes increasingly prevalent (Benjamini, Hochberg 1995). In this study, the choice of the outcome variables to be assessed was pre-informed by both the literature on impact evaluation of similar WASH projects, and by the participatory focus groups with the community. The perception of bad odours in the community is variable that is less frequently considered but is one that is very relevant to the biogas facility. It has proved, arguably, to be the most problematic variable in the dataset.

Our results indicate that, alongside the provision of the small-scale biogas digester itself it is training which facilitates the use of the facilities and which improves the health in households in IUSs. Training, irrespective of distance, increases the use of bio-gas facilities. Proximity to the facilities makes these results stronger. These findings confirm previous suggestions that specific components of sanitation programmes can contribute to improved
health outcomes (Fewtrell, Kaufmann et al. 2005) and that health outcomes can be stronger with interventions that combine multiple dimensions. More specifically they suggest benefits for inclusion a training component when designing, funding and implementing biogas sanitation programmes. Such a component could enhance health outcomes and, when projects are funded by foreign aid, aid effectiveness.
Bibliography

ALVARADO, S.E. and AN, B.P., 2015. Race, friends, and college readiness: Evidence from the High School Longitudinal Study. Race and Social Problems, 7(2), pp. 150-167.

AUSTIN, P.C., 2009. Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. Statistics in medicine, 28, pp. 3083-3107.

BANERJEE, A., DEATON, A. and DUFLO, E., 2004. HEALTH, HEALTH CARE, AND ECONOMIC DEVELOPMENT: Wealth, Health, and Health Services in Rural Rajasthan. The American Economic Review, 94(2), pp. 326-330.

BECERRIL, J. and ABDULAI, A., 2010. The impact of improved maize varieties on poverty in Mexico: a propensity score-matching approach. World Development, 38(7), pp. 1024-1035.

BECKER, S. and CALIENDO, M., 2007. Sensitivity analysis for average treatment effects . The Stata Journal, 7(1), pp. 71-83.

BENJAMINI, Y. and HOCHBERG, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. Journal of the Royal statistical society: series B (Methodological), 57(1), pp. 289-300.

BENSAH, E.C., MENSAH, M. and ANTWI, E., 2011. Status and prospects for household biogas plants in Ghana--lessons, barriers, potential, and way forward. International Journal of Energy & Environment, 2(5), pp. 887-898.

BEVAN, P. and PANKHURST AND FELEKE, T., 2006. Ethiopia Urban Studies - Arada Area Kebele 08/09 Shashemene. Bath: University of Bath: WeD-Ethiopia.

BILLING, D., BENDAHMANE, D. and SWINDALE, A., 1999. Water and Sanitation Indicators Measurement Guide. Washington: USAID.

CALIENDO, M. and KOPEINIG, S., 2008. Some practical guidance for the implementation of propensity score matching. Journal of economic surveys, 22(1), pp. 31-72.

CASEY, K., GLENNERSTER, R. and MIGUEL, E., 2012. Reshaping Institutions: Evidence on Aid Impacts Using a Preanalysis Plan*. The Quarterly Journal of Economics, 127(4), pp. 1755-1812.

CENTRAL STATISTICAL AGENCY, 2011. Analytical Report on the 2011 Urban Employment Survey. Addis Ababa: The Federal Democratic Republic of Ethiopia.

CENTRAL STATISTICAL AGENCY and WORLD BANK, 2013. Ethiopia Rural Socioeconomic Survey (ERSS). Addis Ababa: Central Statistical Agency & the World Bank.
CHAMBERS, R., 2008. From PRA to PLA and pluralism: Practice and theory. In: P. REASON and H. BRADBURY, eds, The SAGE Handbook of Action Research: Participative Inquiry and Practice. Second edn. London: SAGE, pp. 297-318.

CLASEN, T., SCHMIDT, W.P., RABIE, T., ROBERTS, I. and CAIRNCROSS, S., 2007. Interventions to improve water quality for preventing diarrhoea: systematic review and meta-analysis. *BMJ (Clinical research ed.*), 334(7597), pp. 782.

CLEMENS, H., BAILIS, R., NYAMBANE, A. and NDUNG’U, V., 2018. Africa Biogas Partnership Program: A review of clean cooking implementation through market development in East Africa. *Energy for Sustainable Development, 46*, pp. 23-31.

DIPRETE, T.A. and GANGL, M., 2004. Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological methodology, 34*(1), pp. 271-310.

DOIRON, D., FIEBIG, D.G., JOHAR, M. and SUZIEDELYTE, A., 2015. Does self-assessed health measure health? *Applied Economics, 47*(2), pp. 180-194.

EHMKE, M. and SHOGREN, J.F., 2010. The experimental mindset within development economics: Proper use and handling are everything. *Applied economic perspectives and policy, 32*(4), pp. 549-563.

FARR, N.M. and NELSON, B.D., 2014. Child Mortality in Developing Countries. The MassGeneral Hospital for Children Handbook of Pediatric Global Health. Springer, pp. 3-12.

FENN, B., 2012. Impact evaluation in field settings: experience from a complex NGO programme in Ethiopia. *Journal of Development Effectiveness, 4*(4), pp. 566-577.

FEWTRELL, L., KAUFMANN, R.B., KAY, D., ENANORIA, W., HALLER, L. and COLFORD, J.M., 2005. Water, sanitation, and hygiene interventions to reduce diarrhoea in less developed countries: a systematic review and meta-analysis. *The Lancet infectious diseases, 5*(1), pp. 42-52.

FULLERTON, D.G., BRUCE, N. and GORDON, S.B., 2008. Indoor air pollution from biomass fuel smoke is a major health concern in the developing world. *Transactions of the Royal Society of Tropical Medicine and Hygiene, 102*, pp. 843-851.

GOLOVATY, I., JONES, L., GELAYE, B., TILAHUN, M., BELETE, H., KUMIE, A., BERHANE, Y. and WILLIAMS, M.A., 2009. Access to water source, latrine facilities and other risk factors of active trachoma in Ankober, Ethiopia. *PloS one, 4*(8), pp. e6702.

HALLDING, K., LI, Y., WANG, L. and CHEN, Y., 2012. Learning from previous failures: scaling up biogas production in the Chinese countryside. *Climate and Development, 4*(3), pp. 199-209.

HEADEY, D. and ECKER, O., 2013. Rethinking the measurement of food security: from first principles to best practice. *Food security, 5*(3), pp. 327-343.
HECKMAN, J.J., ICHIMURA, H. and TODD, P.E., 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. The review of economic studies, 64(4), pp. 605-654.

HECKMAN, J., ICHIMURA, H., SMITH, J. and TODD, P., 1998. Characterizing Selection Bias Using Experimental Data. Econometrica, , pp. 1017-1098.

ILAHI, N. and GRIMARD, F., 2000. Public Infrastructure and Private Costs: Water Supply and Time Allocation of Women in Rural Pakistan*. Economic Development and Cultural Change, 49(1), pp. 45-75.

JIANG, X., SOMMER, S.G. and CHRISTENSEN, K.V., 2011. A review of the biogas industry in China. Energy Policy, 39(10), pp. 6073-6081.

KAHNEMAN, D. and DEATON, A., 2010. High income improves evaluation of life but not emotional well-being. Proceedings of the National Academy of Sciences of the United States of America, 107(38), pp. 16489-16493.

KHANDKER, S.R., KOOLWAL, G.B. and SAMAD, H.A., 2010. Handbook on impact evaluation: quantitative methods and practices. First edn. Washington, DC: World Bank Publications.

KRUEGER, A.B. and SCHKADE, D.A., 2008. The reliability of subjective well-being measures. Journal of public economics, 92(8), pp. 1833-1845.

LEUVEN, E. and SIANESI, B., 2012. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. S432001 edn. ideas.repec.org: Boston College Department of Economics.

LOHRI, C.R., RODIĆ, L. and ZURBRÜGG, C., 2013. Feasibility assessment tool for urban anaerobic digestion in developing countries. Journal of environmental management, 126, pp. 122-131.

MALUCCIO, J.A., 2004. Using Quality of Interview Information to Assess Nonrandom Attrition Bias in Developing-Country Panel Data. Review of Development Economics, 8(1), pp. 91-109.

MAMO, G., SJAASTAD, E. and VEDELD, P., 2007. Economic dependence on forest resources: A case from Dendi District, Ethiopia. Forest Policy and Economics, 9(8), pp. 916-927.

MISHRA, V. and RETHERFORD, R.D., 2007. Does biofuel smoke contribute to anaemia and stunting in early childhood? International journal of epidemiology, 36(1), pp. 117-129.

O'LOUGHLIN, R., FENTIE, G., FLANNERY, B. and EMERSON, P.M., 2006. Follow-up of a low cost latrine promotion programme in one district of Amhara, Ethiopia: characteristics of early adopters and non-adopters. Tropical Medicine & International Health, 11(9), pp. 1406-1415.
ROSENBAUM, P.R. and RUBIN, D.B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), pp. 41-55.

ROTHMAN, J. and THOMAS, E.J., eds, 1994. *Intervention research: Design and development for human service*. New York: Haworth.

RUBIN, D.B., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational psychology*, 66(5), pp. 688.

RUBIN, D.B. and THOMAS, N., 1996. Matching using estimated propensity scores: relating theory to practice. *Biometrics*, 52, pp. 249-264.

SMITH, L.A. and TODD, P., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1), pp. 305-353.

SMITH, M.T., SCHROENN GOEBEL, J. and BLIGNAUT, J.N., 2014. The financial and economic feasibility of rural household biodigesters for poor communities in South Africa. *Waste Management*, 34(2), pp. 352-362.

THOEMMES, F.J. and KIM, E.S., 2011. A systematic review of propensity score methods in the social sciences. *Multivariate Behavioral Research*, 46(1), pp. 90-118.

TOURANGEAU, R., RIPS, L.J. and RASINSKI, K., 2000. *The psychology of survey response*. Cambridge University Press.

WANJALA, B.M. and MURADIAN, R., 2013. Can big push interventions take small-scale farmers out of poverty? Insights from the Sauri Millennium Village in Kenya. *World Development*, 45, pp. 147-160.

WHITTINGTON, D., JEULAND, M., BARKER, K. and YUEN, Y., 2012. Setting priorities, targeting subsidies among water, sanitation, and preventive health interventions in developing countries. *World Development*, 40(8), pp. 1546-1568.

WHO, 2015. *Global Health Observatory country views - Ethiopia*. Geneva: World Health Organisation.
The project was led by Maltese NGO, KOPIN, in co-operation with an Ethiopian NGO, Women and Children Development Organisation (WCDO). It was financed by the 2011 “Fast-Start Finance – Climate Change”, a foreign aid mechanism, run by the Ministry of Foreign Affairs and the (former) Ministry for Resources and Rural Affairs (Malta).

This consideration is relevant for the plausibility of the ignorability assumption, for should the trained sub-sample differ in unobserved ways from the rest of the community, then even after controlling for differences in observed variables, we cannot be sure whether the results are due to training or due to these unobserved differences.

Two groups were organised, a male group of 8 participants (age 28 – 60), including 5 employed persons (working construction, teaching, market trading, barber), 2 pensioners and 1 unemployed participant, and a female group of 12 participants (age 19-61), including two teachers, four market vendors, one administrative secretary, two housewives and three pensioners. Full results of the PRAs available upon request.

The measurements of typhoid and malaria were based on a formal communication by a medical doctor.

The questionnaire was divided in six parts. The first part included questions on water, sanitation, and hygiene, the second covered household assets and resources, the third part focused on perceptions on environmental quality and governance, the fourth covered respondent physical and mental health, the fifth assessed respondent time management and the sixth basic household demographics.

In the NNM, an individual from the control group (in our case with a limit of n = 5) is selected as a matching partner for a treated individual according to the closest propensity score. The KBM is a non-parametric matching estimator which uses weighted averages of all individuals in the control group to construct the counterfactual match for each participant. This uses more information to match thus lowering the variance. Both statistical significance and manual entering of covariates indicate that the selection methods achieved rigorous matching. The variable ‘religion’ is a set of dummy variables indicating the different religions.

The KBM was undertaken by using a biweight type of kernel.

Unadjusted-Huber White SE: household size .0714-.0669; age .0097-.0096; gender .2765-.2761; measles .3755-.3776; religion .1752-.1552; rooms .1576-.1671; education .2689-.2743

The tables show results for the NMM matching algorithm only, however significance levels for KBM gave identical results in terms of significance and very similar ATTs (available upon request).
Table 1. Community versus Regional means

| Variable          | Description                                      | Sample Community Mean | Population West Arsi Mean |
|-------------------|---------------------------------------------------|------------------------|---------------------------|
| Household size    | Number of people residing in household            | 3.6                    | 3.6                       |
| Age               | Age of respondent                                 | 34.8                   | 37.1                      |
| Measles           | Percentage vaccination against measles            | 17.1                   | 56.2                      |
| Religion          | Percentage of Orthodox                            | 55.3                   | 43.4                      |
| Religion          | Percentage of Christian Protestants               | 34.2                   | 23.5                      |
| Ethnicity         | Percentage of Amhara peoples                      | 21.1                   | 20.3                      |
| Ethnicity         | Percentage of Walayita peoples                    | 26.1                   | 7.8                       |
| Rooms             | Number of rooms in the house                      | 1.5                    | 2.2                       |
| Education         | Percentage with primary education                 | 60.3                   | 61.1                      |
| Education         | Percentage with secondary education               | 21.5                   | 24.5                      |
| Income            | Average monthly household from paid work (Birr)   | 1,079.2                | 1063.4                    |
| Radio             | Percentage owning a radio                         | 60.1                   | 55.4                      |
| Working time      | Hours spent working per week                      | 54.5                   | 45.5                      |
| Malaria           | Percentage ever diagnosed with malaria            | 24.3                   | 20.1                      |
| Typhoid           | Percentage ever diagnosed with typhoid            | 17.7                   | 18.8                      |

Sources: a. Ethiopian Central Statistical Agency and World Bank (2013); b. Bevan, Panhkurst and Fekele (2006).
Table 2. Key variables in the two waves of survey collection

| Variable                           | WAVE 1 |       |       |       | WAVE 2 |       |       |       |
|------------------------------------|--------|-------|-------|-------|--------|-------|-------|-------|
|                                    | Obs    | Mean  | SD.   | Min   | Max    | Obs   | Mean  | SD.   |
| Training                           | 200    | 0.269 | 0.445 | 0     | 1      | 169   | 0.278 | 0.449 |
| Distance from biogas               | 200    | 0.209 | 0.408 | 0     | 1      | 169   | 0.213 | 0.411 |
| Days sick diarrhoea\(^a\)          | 199    | 0.061 | 0.476 | 0     | 5      | 166   | 0.072 | 0.534 |
| Days sick eye infection\(^a\)      | 199    | 1.409 | 4.511 | 0     | 30     | 166   | 0.735 | 3.777 |
| Self-assessed physical health      | 199    | 3.897 | 0.976 | 1     | 5      | 166   | 4.717 | 0.659 |
| Diagnosed with typhoid\(^b\)       | 197    | 0.174 | 0.381 | 0     | 1      | 155   | 0.181 | 0.386 |
| Diagnosed with malaria\(^b\)       | 197    | 0.241 | 0.429 | 0     | 1      | 155   | 0.155 | 0.363 |
| Attitude on bad odours             | 197    | 3.515 | 1.139 | 1     | 5      | 167   | 2.689 | 1.005 |
| Use of new biogas latrine          | 0      | 0.0   | 0.0   | 0     | 0      | 167   | 0.717 | 1.485 |
| Use of new biogas kitchen          | 0      | 0.0   | 0.0   | 0     | 0      | 167   | 1.323 | 1.008 |
| Periods without water\(^c\)        | 198    | 1.041 | 0.817 | 0     | 3      | 167   | 0.701 | 0.707 |

Note: \(^a\) in the last month; \(^b\) in the last year; \(^c\) in the last week.
| Variable    | Description                  | Trained (N=92) | Not-Trained (N=273) | p-values | t-statistics |
|-------------|------------------------------|----------------|---------------------|----------|--------------|
| Household Size | People residing in household | 3.912 u        | 3.412 u             | -0.021 u | -2.143 u     |
|              |                              | 3.873 m        | 4.119 m             | -0.382 m | -0.877 m     |
| Age         | Age of respondent             | 38.164 u       | 31.153 u            | 0.001 u  | -4.312 u     |
|             |                              | 36.126 m       | 33.579 m            | 0.243 m  | -1.184 m     |
| Gender      | Respondent 1 if Male 2       | 1.652 u        | 1.578 u             | -0.093 u | -1.332 u     |
|             | Female                       | 1.638 m        | 1.677 m             | -0.634 m | -0.485 m     |
| Measles     | 1 if vaccinated, 0 if not    | 0.121 u        | 0.227 u             | 0.022 u  | 2.048 u      |
|             |                              | 0.123 m        | 0.112 m             | 0.638 m  | 0.479 m      |
| Religion    | 1 Orthodox 2 Protestant 3    | 1.597 u        | 1.479 u             | -0.062 u | -1.486 u     |
|             | Catholic 4 Muslim             | 1.576 m        | 1.718 m             | -0.212 m | -1.482 m     |
| Rooms       | Number in household          | 1.743 u        | 1.597 u             | -0.101 u | -1.249 u     |
|             |                              | 1.689 m        | 1.656 m             | -0.875 m | -1.261 m     |
| Education   | 1 if primary 0 if none        | 0.531 u        | 0.635 u             | 0.054 u  | 1.611 u      |
|             |                              | 0.552 m        | 0.623 m             | 0.358 m  | 0.163 m      |

Notes: u corresponds to unmatched, m to matched according to propensity scores;
Table 4. Sensitivity analyses before/after matching for key PSM indicators

| Variable                              | Algorithm | Pseudo R2 | p > \chi^2 | Mean SB  | Total % [bias] reduction |
|---------------------------------------|-----------|-----------|-------------|-----------|-------------------------|
| Days sick diarrhoea                   | NNM       | 0.070 b   | 0.000 b     | 23.9 b    | 46.91                   |
|                                       | KBM       | 0.070 b   | 0.000 b     | 23.9 b    | 76.27                   |
| Diagnosed with typhoid               | NNM       | 0.070 b   | 0.000 b     | 24.2 b    | 49.28                   |
|                                       | KBM       | 0.070 b   | 0.000 b     | 24.2 b    | 80.27                   |
| Self-assessed physical health         | NNM       | 0.070 b   | 0.000 b     | 23.9 b    | 51.28                   |
|                                       | KBM       | 0.070 b   | 0.000 b     | 23.9 b    | 77.25                   |
| Use of new biogas latrine            | NNM       | 0.070 b   | 0.000 b     | 23.9 b    | 51.32                   |
|                                       | KBM       | 0.070 b   | 0.000 b     | 23.9 b    | 77.25                   |
| Periods without water                | NNM       | 0.070 b   | 0.000 b     | 24.2 b    | 48.98                   |
|                                       | KBM       | 0.070 b   | 0.000 b     | 24.2 b    | 77.12                   |

Notes: NNM refers to Nearest Neighbour Matching, KBM refers to Kernel Based Matching; b refers to before matching, a after matching procedures were undertaken.
Table 5. Impacts of training on health indicators

| Variable                        | ATT       | t-statistic | p-value | $\Gamma_{rb}$ | $\Gamma_{mh}$ | N(treat.) | N(contr.) |
|---------------------------------|-----------|-------------|---------|---------------|---------------|-----------|-----------|
|                                 |           |             |         |               |               |           |           |
| Self-assessed physical health   | 0.31 (A)  | 2.23 (A)    | 0.05    | 2 (A)         | 2 (A)         | 85 (A)    | 268 (A)   |
|                                 | 0.83 (C)  | 3.06 (C)    | 0.01    | 2 (C)         | 2 (C)         | 23 (C)    | 30 (C)    |
|                                 | 0.25 (F)  | 1.33 (F)    | 0.32    | 2 (F)         | 2 (F)         | 44 (F)    | 238 (F)   |
| Diagnosed with typhoid          | -0.04 (A) | -0.61 (A)   | 0.21    | - (A)         | 1 (A)         | 83 (A)    | 259 (A)   |
|                                 | -0.22 (C) | -2.11 (C)   | 0.10    | - (C)         | 1.5 (C)       | 23 (C)    | 30 (C)    |
|                                 | 0.00 (F)  | 0.00 (F)    | 0.45    | - (F)         | - (F)         | 42 (F)    | 229 (F)   |
| Days sick diarrhoea             | -0.07 (A) | -1.01 (A)   | 0.76    | 1 (A)         | 2 (A)         | 85 (A)    | 267 (A)   |
|                                 | 0 (C)     | 0 (C)       | 0.65    | - (C)         | - (C)         | 3 (C)     | 30 (C)    |
|                                 | -0.13 (F) | -1.01 (F)   | 0.82    | 1 (F)         | 1 (F)         | 44 (F)    | 237 (F)   |
| Diagnosed with malaria          | -0.06 (A) | -0.97 (A)   | 0.21    | - (A)         | - (A)         | 83 (A)    | 259 (A)   |
|                                 | -0.17 (C) | -1.77 (C)   | 0.10    | - (C)         | 1.1 (C)       | 23 (C)    | 30 (C)    |
|                                 | -0.02 (F) | -0.26 (F)   | 0.29    | - (F)         | 1 (F)         | 42 (F)    | 229 (F)   |
| Eye infections                  | 0.52 (A)  | 0.82 (A)    | 0.80    | 1 (A)         | 2 (A)         | 85 (A)    | 267 (A)   |
|                                 | 0.48 (C)  | 0.71 (C)    | 0.91    | 1 (C)         | 1 (C)         | 23 (C)    | 30 (C)    |
|                                 | 0.43 (F)  | 0.39 (F)    | 0.76    | 1 (F)         | 1 (F)         | 44 (F)    | 237 (F)   |
| Perceived odours                | -0.39 (A) | -2.18 (A)   | 0.05    | 2 (A)         | 2 (A)         | 85 (A)    | 268 (A)   |
|                                 | -1 (C)    | -3.08 (C)   | 0.01    | 2 (C)         | 2 (C)         | 23 (C)    | 30 (C)    |
|                                 | -0.04 (F) | -0.17 (F)   | 0.21    | 1 (F)         | 1 (F)         | 44 (F)    | 238 (F)   |
| Biogas latrine use              | 1.12 (A)  | 5.36 (A)    | 0.01    | 2 (A)         | 2 (A)         | 85 (A)    | 268 (A)   |
|                                 | 1.65 (C)  | 3.46 (C)    | 0.01    | 2 (C)         | 2 (C)         | 23 (C)    | 30 (C)    |
|                                 | 0.59 (F)  | 2.44 (F)    | 0.05    | 2 (F)         | 2 (F)         | 44 (F)    | 238 (F)   |
| Biogas kitchen use              | 0.56 (A)  | 3.50 (A)    | 0.01    | 2 (A)         | 2 (A)         | 85 (A)    | 268 (A)   |
|                                 | 0.72 (C)  | 1.91 (C)    | 0.10    | 2 (C)         | 2 (C)         | 23 (C)    | 30 (C)    |
|                                 | 0.38 (F)  | 1.90 (F)    | 0.10    | 2 (F)         | 2 (F)         | 45 (F)    | 238 (F)   |
| Periods without water           | 0.06 (A)  | 0.48 (A)    | 0.32    | 2 (A)         | 1.7 (A)       | 85 (A)    | 268 (A)   |
|                                 | -0.13 (C) | -0.53 (C)   | 0.43    | 1 (C)         | 1 (C)         | 23 (C)    | 30 (C)    |
|                                 | 0.14 (F)  | 0.76 (F)    | 0.85    | 1 (F)         | 1 (F)         | 44 (F)    | 238 (F)   |

Note: (A) refers to All community members, (C) households who live Close, and (F) those who live Far from the biogas facilities.