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Abstract

The outcome of household choice depends on the private information available to an agent, particularly in terms of costs and benefits. This study examines the role of information in the adoption of clean cooking fuel in Bhutan. We use a rural subsample of nationally representative data from the 2012 Bhutan Living Standard Survey (BLSS) conducted in all twenty districts. We estimate a bivariate probit model to control for the potentially endogenous information variable. The results indicate that households that have access to information are approximately 40 percent more likely to adopt clean cooking fuel. Similarly, households are 49 percent less likely to adopt dirty fuel (firewood) when exposed to information. Other factors such as education, the electricity supply, access to liquidity and the distance to the market are important factors that contribute to adopting clean cooking fuel. The results also show that the effect of information varies depending on the level of education of the household heads, thus highlighting the importance of accounting for the level of education of information recipients when designing a similar information provision.

Key Words: clean fuel, information, operator, environment, indoor air pollution

JEL Code: Q50, Q55,

1. Introduction

The International Energy Agency (IEA, 2015) has reported that approximately 2.7 billion people depend on solid fuels as a source of energy for cooking and heating. The combustion of solid fuel with an inefficient cookstove is the primary cause of indoor air pollution (IAP), especially in developing countries (Jeuland, Pattanayak, & Bluffstone, 2015; Smith, Mehta, & Maeusezahl-Feuz, 2004). The problem of IAP has been identified as the prominent source of environmental health hazards, responsible for the premature deaths of 4.3 million people in 2012 (WHO, 2014) and 5 percent of the global burden of disease, expressed in terms of disability-adjusted life years (DALYs) (Anenberg et al., 2012). Put differently, IAP causes more premature deaths than HIV/AIDS, malaria, and tuberculosis combined (Putti, Tsan, Mehta, & Kammila, 2015).

Furthermore, firewood in developing countries is usually collected by women and children, at the cost of other productive activities (Duflo, 2008 & Nepal, 2011). This mode of collection leads to a reduction in women's contribution to the household budget; additionally, children's educational performance may be hindered, and they occasionally may even be prevented from attending school (Khan & Lyon, 2015; Malla, Bruce, Bates & Rehfuess, 2011 & Kumar & Viswanathan, 2007). Mala et al. (2011) also shows substantial benefits for women and children in terms of the time saved not collecting firewood. However, it is predicted that without sufficient policy interventions, the trend of combusting biomass for cooking in developing countries is expected to remain as an important environmental and public health issue until 2030 (IEA, 2012). Numerous studies including Malla et al. (2011) and Kumar and Viswanathan (2007) have shown that the reason for the popularity of firewood dependence is associated with affordability and easy access. Therefore, there is a need to reinforce policies on a regular basis based on how economic, social and household attributes affect the adoption of clean cooking fuel in the heterogeneous settings of developing countries.

In Bhutan, according to the 2016 Annual Health Bulletin, respiratory diseases have been reported as one of the top three diseases (MoH, 2016). The same report also states that approximately 1000 out of every 10,000 children under the age of five were infected with pneumonia, which is closely associated with poor indoor air quality, thus indicating the presence of IAP problems. This evidence is further supported by a small-sample study conducted in Bhutan by Wangchuk et al. (2017), who reported that when traditional cookstoves were operated, PM2.5 and CO increased, on average, by 40 and 18 times, respectively. Another study has reported that children's exposure to ultrafine particles was high during cooking hours (Wangchuk et al., 2015). The prevalence of a high concentration of carbon monoxide in Kenya and Nepal, where biomass was predominantly used for cooking in pretreatment households, has also been reported by Malla et al. (2011). Hence, the high incidence of respiratory diseases in Bhutan can be linked to the poor indoor air quality.

In response to the above threats posed by the combustion of solid fuels and inefficient cookstoves, governments and nongovernmental organizations (NGOs) have disseminated improved cookstoves (ICS) in developing countries. Similarly, in Bhutan, ICS and biogas were first disseminated in the 1980s but without much success due to a lack of maintenance know-how (UNDP, 2008). However, in 2008, the Bhutan Sustainable Rural Biomass Energy (BSRBE) project was launched in partnership with the UNDP[1] and the government of Bhutan to promote and distribute ICS in rural villages. In addition, the Bhutan government initiated the Bhutan Biogas Project (BBP) in 2011 to promote biogas plants in rural areas. Despite all these interventions in place, available reports suggest that rural households still suffer from the problem of IAP.

In addition to the above interventions, one of the policy interventions for overcoming the problem of IAP is to improve access to clean cooking fuel with an affordable price. Bhutan has made significant

[1] UNDP stands for United Nation Development Programme.

progress in rural electrification during the last few decades. According to Kumar and Rauniyar (2011), Bhutan began its rural electrification program, which was aimed at improving overall health and quality of life (ADB, 2007), as early as 1990. As of 2015, Bhutan has achieved 100 percent rural household electrification (BPC, 2015), up from 23 percent of total households having access to electricity in 2003 (NSB, 2007). Electricity up to 100 units per household is also provided for free in rural areas (BPC, 2017). Similarly, road networks also increased from 3690 km (RGOB, 2000) in 2000 to 11,177 km in 2016 (RGOB, 2016), improving access to clean cooking fuels such as liquid petroleum gas (LPG).

The literature on fuel adoption suggests that education, income, accessibility and price play an important role in the adoption of cooking fuel. While these factors seem to be very important, agents may respond differently to the adoption of household cooking fuel when they decide in light of better information, particularly when agents are well informed about the (costs) benefits of using clean (dirty) cooking fuel. Considerable evidence has shown that individuals or agents behave differently when information is made available to them. For instance, the energy consumption of households decreases when households are treated with information about energy price increases (Jessoe & Rapson, 2014), disclosing the quality (state of the art) of automobiles helps the bidder participation decision in auctions (Tadelis & Zettelmeyer, 2015), information about the benefits of a tax deferred account increase the take-up rate (Duflo & Saez, 2003), and scientific information increases the approval of a supply organ (Elias et al., 2015). There are many channels through which households may acquire information or knowledge about the harmful effects of IAP, and television is one of the most important sources of information and knowledge. Despite the general consensus on the important role of information in adopting cooking fuel and ICS, to the best of our knowledge, there is no evidence regarding how information disseminated through television affects the adoption of clean cooking fuel, and our study is an attempt to fill this knowledge gap. Simultaneously, cooking fuels that are high in the energy ladder such as LPG and electricity are considered to be for the urban rich, and poor rural households have been ignored by policy (Smith & Sagar, 2014). Our study provides evidence of clean fuel adoption by rural poor and may be helpful in considering the inclusion of clean fuel in the fuel basket of rural households using household data from Bhutan.

The major contributions of this paper are manifold. First, we shed light on the role of information disseminated through television in the adoption of clean fuel. This study estimates the effect of information disseminated through television on the adoption of clean cooking fuel by considering the issue of endogeneity of television ownership by using an instrumental variable approach. In addition, we control for distance variables such as the distance to the market and to the forest. We consider that controlling for the distance variable is important because in rural developing countries, clean fuels such as LPG and related accessories are usually available only in urban areas and the distance to the market measures the household's accessibility to clean fuel. Similarly, the distance to the forest matters to rural households because they usually collect firewood from the nearest forest. In this regard, our paper also differs from the previous studies on fuel adoption conducted in Bhutan by Rahut, Behera and Ali (2016) and Rahut, Das, De Groote and Behera (2014). Both of these studies have extensively covered identifying the factors that contribute to the adoption of cooking, heating and lighting fuel. However, in both of these studies, the authors have ignored the distance to the forest, which we account for.

One of the strengths of our study is that we have access to a very rich dataset, namely, the Bhutan Living Standard Survey (BLSS) 2012. The BLSS 2012 is a nationally representative dataset covering households from all twenty districts in Bhutan. In addition, it has a large sample size of approximately 4349 households from rural Bhutan, and it has information about the location of its respondents, which allowed us to construct an instrumental variable from another dataset.

This paper is arranged as follows: Section 2 briefly describes the background of access to information in Bhutan; Section 3 describes the theory and estimating strategy; Section 4 reports the data and variables; Section 5 discusses the results; and Section 6 concludes the paper.

2. Brief Background: Access to Information in Bhutan

In developing countries, households generally acquire information through television, radio, and interactions (phone or in person) and from various government awareness programs. In high-literacy areas, households may also acquire information from reading materials such as newspapers or books. In rural Bhutan, the literacy rate is relatively low. According to the BLSS 2017 (NSB, 2017) report, the rural literacy rate is 58 percent, indicating that approximately half of the population cannot read and write. Thus, we can safely assume that television is one of the most important sources of information in rural Bhutan.

In Bhutan, television broadcasting was officially launched in 1999 (Rapten, 2001), and currently, there are two government-owned national television channels, locally known as BBS 1 and BBS 2 (Bhutan Broadcasting Service 1 and 2) (BICMA, 2015). In addition to television, Bhutan has 10 newspapers. All of these newspapers have nationwide coverage, but readership is limited to urban areas due to the low literacy rate in rural areas.

The national television channel BBS 2 is oriented towards business and entertainment, while BBS 1 focuses purely on news, public announcements and educational programs. These educational programs cover a vast array of topics including the environment, health, education, religion, agriculture, politics and the economy[2] (Tiwa, 2016). These programs are delivered in different formats, ranging from news to debates, documentaries, panel discussions and question and answer (Q&A) sessions. For instance, a recent BBS program covered the adoption of biogas in rural households in 2011[3] and the adoption of ICS in rural parts of Bhutan in 2016[4], particularly focusing on the health, environmental and economic benefits of the interventions (Tiwa, 2016). Health programs on various diseases including respiratory diseases are also broadcast on a regular basis. According to Tiwa (2016), such important public issues are covered by news reports and Q&A sessions with physicians explaining the causes, symptoms and prevention techniques of such diseases. Similarly, when the BSRBE, BPP and rural electrification programs were launched several years ago, the objectives of these programs such as improving quality of life, the importance of conservation and health benefits were covered in the form of a news brief and panel discussions (Tiwar, 2016). In addition, the BBS also has a mandate to educate and create awareness, and therefore, BBS programs regularly disseminate information on other government programs such as those related to waste management, sanitation, health, and organic agriculture.

In addition to the BBS channels, households have access to many global and regional television channels such as the BBC, CNN, AXN, Discovery, and National Geographic as well as channels from neighboring countries such as Bangladesh, India and Nepal. According to Oyama and Lhamo (2015), households have access to approximately 40 different international channels. For households, these channels also act as a source of information about new products such as LPG and electric cookstoves as well as other electrical appliances advertised in commercials.

Therefore, based on the above evidence, it is our plausible assumption that if households own a television, then they are exposed to information about the importance of environmental conservation, the health benefits and harmful effects of IAP and other government programs. However, in this study, we

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[2] Ashok Tiwa is the chief editor of the BBS. Since there is no information about past television programs broadcast by BBS1 and BBS 2, I interviewed him about the BBS's past programs. All information about past BBS programs were collected through this interview.

[3] The news brief on biogas adoption is available at the following BBS webpages: http://www.bbs.bt/news/?p=20899 and http://www.bbs.bt/news/?p=6789.

[4] The news brief about ICS is available at the following BBS webpage: http://www.bbs.bt/news/?p=64543.

reserve judgment regarding the channel through which this information affects the household decision on adopting cooking fuel.

3. Theory and Estimation Strategy

Following utility theory, we assume that household *i* chooses cooking fuel from the available fuel basket when utility (benefit) $U_i^c > U_i^d$, where U_i^c and U_i^d are the utility from using clean fuel *c* (such as LPG and electricity) and dirty fuel d (firewood), respectively. The utility from cooking fuel adopted by households is not observed, and only the fuel adopted by households is observed. In other words, choices are made based on latent variables, which are a measure of random utility. The latent variable model is as follows:

$$y_i^* = \theta TV_i + \boldsymbol{x_i \beta} + u_i \tag{1}$$

where ($y^* = U_i^c - U_i^d$ and) $y = 1\ [y^* > 0]$ and 0 otherwise is an estimation equation where **x** is a vector of exogenous control variables and TV is a variable indicating whether the household owns a *television*; and $\theta$and $\boldsymbol{\beta}$ are parameters to be estimated.

In the BLSS data, whether households are treated with information is not directly observed. However, based on the discussion in Section 2, we assume that households that own a *television* are treated with information about the importance of environmental conservation, the health benefits of clean fuel, the diseases caused by IAP and the availability of alternative fuels. However, the ownership of a *television* is not randomly assigned, and it is likely that unobserved factors that explain *clean cooking fuel* adoption may also be correlated with the adoption of *television*. It is possible that unobservable covariates that affect the adoption of *clean cooking fuel* and *television* are closely related to the adoption of any type of new technology since the use of *clean fuel* involves using modern cookstoves and electrical appliances. Therefore, factors such as attitude and a preference for technology, operational knowledge and past experiences using a similar technology, which are usually not observed by researchers, may be correlated with the variable *television*, and *television* is potentially an endogenous variable.

The dependent variable in Equation 1 is binary and leads to the estimation of the standard probit or logit model if there is no endogeneity issue with the explanatory variables. However, as noted above, television is potentially an endogenous variable, and the error term u_i in Equation 1 may be correlated with the variable *TV (Television)*. The endogenous variable is also a binary variable taking the value of 1 if the household has adopted a *television* and 0 otherwise, which leads to the estimation of another model on adoption of a *television*:

$$TV_i^* = \delta Z_i + \boldsymbol{x}_i \boldsymbol{\alpha} + v_i \tag{2}$$

where $TV = 1[TV^* > 0]$ and 0 otherwise, **x** is a vector of exogenous variables that explain the adoption of *television* (TV) and v_i is an error term. In Equation 2, Z is an instrumental variable that satisfies the conditions of relevancy and exogeneity; that is, Z and TV are partially correlated but Z is uncorrelated with the error term in Equation 1. The validity of this assumption is briefly reported in the results and discussion section.

We use the variable *operator* as an instrument for the endogenous variable *television*. It is constructed using information about the availability of television cable operators in different parts of the sub-districts (*chiwog*) of Bhutan. They provide television cable services where households have the option to subscribe to television channels with a monthly premium. However, not all households have access to these services because there are no such cable operators in the sub-district in which people live. In areas where these services are not available, households use a satellite antenna to watch television programs. The data on the availability of such services are not available in BLSS 2012; however, the Ministry of

Information and Communication of Bhutan (MoIC), an agency responsible for regulating media entities, has a list of television cable operators by the geographical areas in which they operate. The variable operator is defined as 1 if a particular sub-district (*chiwog*) has a television cable operator based on the MoIC list.

It is our assumption that if households have the option to access television cable services, households are more likely to adopt television because they do not have to make an additional investment in a satellite antenna. However, we cannot find any reasonable explanation of how having an option to an available television cable service will directly explain the adoption of cooking fuel. Therefore, two adoption equations are estimated jointly by allowing the error terms u_i and v_i to have an arbitrary correlation. Assuming that the error terms (u_i and v_i) have a bivariate normal distribution with a zero mean and unit variance, Equations 1 and 2 are estimated as a bivariate probit model. The partial effect of information (*television* ownership) on choosing *clean fuel* is as follows:

$$Prob(y = 1|TV, \boldsymbol{x}) = \Phi(\boldsymbol{x\beta} + \theta) - \Phi(\boldsymbol{x\beta}) \tag{3}$$

where y stands for *clean fuel* and Φ is the standard normal cumulative distribution function (CDF). In the above model, only the adoption of clean cooking fuel is described. However, adoption models for *LPG*, *electricity* and *firewood* are also estimated in our study, and the same discussion applies to all models. We assume that households that own a *television* will acquire information about the consequences of burning *firewood*, and we expect a positive coefficient for the variable *television*, indicating that better informed households are more likely to adopt *clean fuel*, holding other factors constant. The rest of the variables are discussed in Section 5, in addition to the coefficients of the respective variables.

4. Data and Variables

We use data from the BLSS conducted in 2012 by the National Statistics Bureau of Bhutan (NSB). The BLSS 2012 surveyed 8968 households from all twenty districts. The BLSS 2012 covers information at both the individual and household levels on demography, education, health, employment, housing, expenditures and income. The Population and Housing Census of Bhutan 2005 was used to construct primary sampling units (PSUs) in rural and urban areas. Blocks were used as PSUs for urban areas, while chiwogs (sub-districts, the lowest administrative units) were used as PSUs for rural areas. The households were randomly selected from each PSU based on a probability proportional to size from the PSUs (NSB, 2012).

The BLSS 2012 reports that in rural Bhutan, 45, 76 and 51 percent of households use *LPG*, *electricity* and *firewood*, respectively, for cooking[5]. In urban Bhutan, it was reported that approximately 92, 98 and 2 percent use *LPG*, *electricity* and *firewood*, respectively. In our study, "*clean fuel*" is defined based on the following question: "What fuel do you use most often for cooking?" Households were asked to provide the two most frequently used cooking fuels without maintaining the order of the first and second most frequently used cooking fuels. This method of collecting information on fuel use has both advantages and disadvantages. One of the advantages of eliciting fuel use from this question is that it is possible overcome the difficulty of ranking the first and second most frequently used cooking fuels. The difficulty of ranking fuels may arise if households use two fuels simultaneously at an almost equal proportion or with little variation. Similarly, if households use two fuels at an equal proportion or with little variations, the

[5] Less than 2 percent of households reported using coal and kerosene for cooking, and these households were included in the firewood user category. The total percentage of LPG, electricity and firewood exceeds 100 percent because we used the same definition of LPG, electricity and firewood users as that in the BLSS report. The BLSS classified households as LPG users if they reported using LPG as their first or second most frequently used fuel and similarly for the others.

response to this question may not reflect the true fuel rank. One of the disadvantages of eliciting fuel usage in this way is the inability to identify which is the most important fuel for the household. The literature suggests that fuel stacking is common in developing countries, and the case of Bhutan is no different. In this study, we categorize households as clean cooking fuel users only if both cooking fuels reported were either *LPG* or *electricity*, following the method used by the NSB. Similarly, the variable *LPG* is defined as 1 if one of the two fuels reported was *LPG* and similarly for the rest of the fuels. As a result, the total percentage of *LPG*, *electricity* and *firewood* users exceeds 100 percent.

Table 1
Definitions of Variables and Summary Statistics

Variable	Definition	Mean	SD
Dependent Variables:			
Clean Fuel	1 if LPG and electricity are used for cooking	0.411	0.492
LPG	1 if LPG is used for cooking	0.448	0.497
Electricity	1 if electricity is used for cooking	0.760	0.427
Firewood	1 if firewood is used for cooking	0.508	0.500
Independent Variables:			
Television	1 if the household owns a television	0.379	0.485
Electrified	1 if the house is connected to electricity	0.825	0.380
Primary	1 if the head of household completed 6 years of education	0.112	0.315
Secondary	1 if the head of household completed 12 years of education	0.085	0.278
University	1 if the head of household completed more than 12 years of education	0.035	0.183
Read	1 if the head of household can read and write	0.341	0.474
Age	The age of the head of household, in years	49.13	15.33
Female	1 if the head of household is female	0.345	0.475
Children	1 if the household has a child below the age of six	0.374	0.484
Size	The total number of household members	4.783	2.223
Loan	1 if the household had taken a loan from a bank	0.247	0.431
Expenditure	Monthly per capita household expenditures	163.9	695.8
Market	Distance to the market, in hours	1.726	5.737
Forest	Distance to the forest, in hours	0.948	2.091
Operator	1 if the sub-district has a television cable operator	0.108	0.310
Number of Districts	20		
Observations	4349		

One of the variables of interest is whether households own a *television*. In the rural subsample, approximately 38 percent of households reported having a *television*. Additionally, approximately 83 percent of households have access to an electricity grid connection. The level of education of the head of household is low, as only approximately 11 percent reported having completed primary school, nine percent secondary school and four percent university education. The definitions and summary statistics of the variables are reported in Table 1. The correlation matrix is available upon request.

5. Results and Discussion

5.1 Instrument Validity and Television Adoption

In this subsection, we first briefly discuss the validity of the instrument and present the results on television adoption. In the following subsections, we report the results on the adoption of clean cooking fuel, the robustness checks for the results and the policy discussion.

As discussed above, there is potentially an endogenous variable in our models, and thus, the results depend on the validity of the instrument, that is, the variable *operator*. However, given the nature of dependent and endogenous variables, we cannot perform the standard exclusion restriction test. Our results show that ρ, the correlation between the error terms of Equations 1 and 2, is significant at a conventional level, as reported in Table 2, for all models. This result suggests that there is evidence for endogeneity. In

Table 2, for all models, the variable *operator* is significant at the one percent level and confirms the relevancy condition $Cor(TV, Z) \neq 0$.

We first interpret the results of Equation 2, in which the dependent variable is *television* ownership. For all models, the coefficients of the explanatory variables of Equation 2 are comparable in terms of their signs and levels of significance, and we interpret the results of Equation 1 from all models together in this subsection. As expected, the coefficient of the education variables *primary*, *secondary* and *university* are positive, suggesting that households headed by better educated individuals are more likely to adopt *television*. Similarly, the variables *electrified*, *size* and *loan* are also positive. If households are *electrified* and household have access to liquidity (*loan*), then households are more likely to adopt *television*. The distance to the *market* is negative, as expected, indicating that when households are located farther away from urban amenities, households are less likely to adopt *television*. The variable *operator*, which indicates the availability of a television cable operator, is positive and significant, as expected, indicating that the presence of television cable services increases the likelihood of adopting *television*.

5.2 Clean Fuel Adoption

In this subsection, we report the results of the *clean fuel* model from Table 2. As noted above, *television* is our variable of interest, which we use as a proxy for households having access to *information*. As expected, the coefficient of *television* is positive and significant at the 1 percent level, indicating that households that have access to information are more likely to adopt *clean fuel* for cooking than those that do not have access, assuming other factors remain constant.

The level of education also has a positive effect on the adoption of *clean fuel*, as expected. Household heads with *primary*, *secondary* and u*niversity* education are more likely to adopt clean fuel than those comprising the reference category, who do not have any form of educational training, all other factors remaining constant. Studies conducted by Heltberg (2005) in Guatemala and by Alem, Beyene, Kohlin and Kekonnen (2016) in Ethiopia have also found that education is an important determinant for adopting clean fuel. For other household attributes, such as *female*-headed households and the presence of *children* below the age of six, we expected positive coefficients. The reason is that in developing countries, women are usually responsible for collecting firewood and the presence of children (below age six) prevents them from collecting firewood (Amacher, Hyde, & Joshee, 1993; Heltberg, Arndt, & Sekhar, 2000; Nepal, Nepal, & Grimsrud, 2011). Such practices are also common in Bhutan. Similarly, women are also responsible for cooking in developing countries, and it has been reported that *female*-headed households show a strong preference for clean cooking fuel (Amacher et al., 1993; Israel, 2002; Rahut et al., 2016). The coefficient of *female* is positive, as expected, and significant. The variable *child* is not significant, and this result is comparable to that of Nepal et al. (2011), who reported in their study that the presence of a *child* was not significant after correcting for the endogeneity of the fuel collection time.

Numerous studies, including those by Heltberg (2005) and Nepal et al. (2011) that more household members have reported a negative effect on adopting clean fuel, as these households have more labor force for collecting firewood. The coefficient of household size is negative and significant at the one percent level, thus indicating that households with more members are less likely to adopt clean fuel. We also control for access to liquidity, which is measured in terms of having accessed loan services from financial institutions. The coefficient is positive, as expected, and significant, suggesting that access to liquidity has a positive effect on adopting clean cooking fuel. Similarly, Edward and Langpap (2005) in Guatemala also found that access to credit leverages households to purchase gas stoves and has a negative effect on the use of firewood in a household. However, these authors suggest that a subsidy would be more effective, as their simulation results found only a marginal effect of having access to credit.

Table 2
Bivariate Probit Results of Cooking Fuel

	Clean Fuel Model		LPG Model		Electricity Model		Firewood Model	
Variables	Clean Fuel	Television	LPG	Television	Electricity	Television	Firewood	Television
Television	1.506***		1.422***		1.083***		-1.758***	
	(0.145)		(0.176)		(0.312)		(0.087)	
Electrified	1.543***	0.723***	0.602***	0.735***	2.333***	0.733***	-1.094***	0.733***
	(0.154)	(0.074)	(0.092)	(0.074)	(0.163)	(0.074)	(0.105)	(0.073)
Primary	0.242***	0.168**	0.277***	0.170**	0.058	0.163**	-0.094	0.166**
	(0.078)	(0.068)	(0.076)	(0.068)	(0.098)	(0.069)	(0.072)	(0.068)
Secondary	0.320***	0.844***	0.447***	0.838***	-0.112	0.854***	-0.205*	0.851***
	(0.114)	(0.087)	(0.122)	(0.088)	(0.167)	(0.088)	(0.106)	(0.087)
University	1.009***	1.157***	1.250***	1.164***	0.132	1.157***	-1.096***	1.172***
	(0.181)	(0.122)	(0.217)	(0.124)	(0.251)	(0.123)	(0.231)	(0.124)
Age	0.000	-0.001	0.000	-0.000	-0.005**	-0.001	0.006***	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.143***	0.056	0.130**	0.054	-0.022	0.053	-0.024	0.052
	(0.053)	(0.049)	(0.052)	(0.049)	(0.065)	(0.049)	(0.050)	(0.049)
Children	-0.005	0.057	-0.002	0.057	0.019	0.055	0.004	0.043
	(0.054)	(0.050)	(0.052)	(0.050)	(0.066)	(0.050)	(0.051)	(0.049)
Size	-0.048***	0.047***	-0.039***	0.046***	-0.035**	0.046***	0.080***	0.045***
	(0.012)	(0.011)	(0.012)	(0.011)	(0.015)	(0.011)	(0.012)	(0.011)
Loan	0.275***	0.308***	0.298***	0.305***	0.090	0.303***	-0.110**	0.300***
	(0.060)	(0.050)	(0.062)	(0.050)	(0.082)	(0.050)	(0.056)	(0.050)
Expenditure (*ln*)	-0.032	-0.021	-0.011	-0.021	-0.051*	-0.021	0.099***	-0.021
	(0.022)	(0.019)	(0.021)	(0.019)	(0.026)	(0.019)	(0.020)	(0.019)
Market (*ln*)	-0.152***	-0.108***	-0.145***	-0.109***	-0.109***	-0.105***	0.095***	-0.108***
	(0.021)	(0.017)	(0.021)	(0.017)	(0.030)	(0.017)	(0.018)	(0.017)
Forest (*ln*)	0.007	0.001	0.005	-0.000	-0.047	-0.002	-0.003	-0.000
	(0.030)	(0.025)	(0.029)	(0.025)	(0.036)	(0.025)	(0.028)	(0.025)
Operator		0.336***		0.330***		0.299***		0.405***
		(0.077)		(0.076)		(0.077)		(0.073)
Constant	-1.633***	-0.675***	-0.390	-0.694***	-1.177***	-0.672***	0.349	-0.702***
	(0.246)	(0.203)	(0.248)	(0.204)	(0.288)	(0.205)	(0.227)	(0.201)
Observations	4349	4349	4349	4349	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ρ	-0.530***		-0.528***		-0.394*		0.923***	
	(0.122)		(0.145)		(0.222)		(0.123)	
Loglikelihood	-4092		-4245		-3492		-4151	

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

The results on the effect of income on fuel adoption are mixed. For instance, Heltberg (2005) found that household per capita expenditure had a significant and positive influence on the adoption of *LPG* in an urban subsample and no effect on a rural subsample in Guatemala. Similarly, a study in a Shangzhu village in China by Chen, Heerink, and van den Berg (2006) reported that income had no effect on either fuelwood collection (per day) or the time spent on collecting firewood (labor input). Consistent with the above studies, per capita household expenditure is not significant. However, Farsi, Fillippini and Pachauri (2007) have found that in urban India, richer households are more likely to adopt clean fuel. Simultaneously, one influential paper by Kumar and Viswanathan (2007), who investigate the environmental Kuznets curve using a large dataset from India, has shown that the probability (and quantity) of consuming dirty fuel increases with an increase in income. Similarly, a study conducted in rural India by Hanna and Oliva (2015) has reported that a wealth transfer (which might have a direct impact on household expenditure or income) increases the consumption of dung cake and kerosene and reduces the consumption of firewood, thus indicating that households tend to replace their current dirty fuel with a newly available dirty fuel as they become wealthier.

We also control for access to energy amenities by including the distance to the market and to the forest. In Bhutan, *LPG* is not directly supplied to households through pipe networks, and therefore, households have to refill their empty *LPG* cylinder at a distribution depot, usually located in the nearest market. Therefore, the distance to the nearest *market* measures the accessibility of clean fuel. On the other hand, firewood is directly collected from the nearest *forest*, making it possible to measure the availability of firewood. The coefficient of market is significant and negative, as expected, indicating that as households live farther away from the market, they are less likely to adopt clean fuel. However, the distance to the forest is not significant. This result may be due to the abundance of firewood in rural Bhutan, as approximately 70 percent of the country is still under forest cover. However, Heltberg (2005) reported that the distance to the forest was significant at the five percent level, which may be due to the scarcity of firewood in Guatemala.

We further estimate additional models by adding the interaction of *television* and the level of education, as we assume that a minimum level of educational training may be necessary for information to influence the fuel adoption decision. The results are reported in Table 3, Panel A, and the results show that the variable *television* is still significant at the 1 percent level. The interaction of *television* with *primary* and *secondary* schooling is not significant, but the interaction with *university* education is significant, indicating that a minimum level of education is necessary for information to become more effective. Additionally, in Model 4 (of Table 4), the education variables are replaced by the variable *read*, indicating whether the head of household can read and write. In Bhutan, there is a system of monastic education and a so-called non-formal education system where the government provides free lessons for those wishing to learn as part of a life-long learning program, and therefore, not having formal educational training does not necessarily mean that people cannot read and write. Therefore, even if they have reported zero years of schooling, there is still a possibility that some can read and write and process information. As expected, the interaction variables with *television* and *read* are significant, indicating that households headed by an individual who can *read* and write and households that own a *television* are more likely to adopt *clean fuel*.

5.3 Robustness Checks

To test the robustness of the results of the *clean fuel* model reported in Table 2, we first estimate an ordinary probit model for *clean fuel* by ignoring the endogeneity of *television* ownership. Next, we use the control function method to examine the effect of information provision, following the method described by Woldrige (2015) and Terza, Basu and Rathouz (2008). The results are reported in Appendix A1, Table A2. In the control function approach, we first estimate the first-stage probit model for *television* ownership using the variable *operator* as an instrument by including all explanatory variables used in the bivariate probit model. In the second stage, we estimate the model for *clean fuel* by including the residuals from the first-stage probit model (the results are reported in Table A2, Column 3). In the control function approach, we also allow *television* to have an arbitrary correlation with residuals by including the interaction of *television* and residuals, and we estimate what Woldridge (2015) calls the correlated random coefficients (the results are reported in Table A2, Column 4). Finally, we add the squared term for the residuals to account for the nonlinearity of residuals (and the results are reported in Table A1, Column 5). In all of the estimation methods and specifications that we used, the coefficient of *television* is positive and significant at a conventional level.

We further estimate three different bivariate probit models separately for the adoption of each cooking fuel: *LPG*, *electricity* and *firewood*; we refer to these models as the *LPG*, *electricity* and *firewood* models, respectively. We also account for the endogenous variable television and estimate a bivariate model for all three cooking fuels. The results are reported in Table 2 as the *LPG*, *electricity* and *firewood* model.

Table 3
Bivariate Probit Results of Each Fuel with Interaction Variables

Variables	Model 1 (Primary)	Model 2 (Secondary)	Model 3 (University)	Model 4 (Read)
Panel A: Results of clean fuel with interaction variables				
Television	1.526***	1.509***	1.536***	1.386***
	(0.145)	(0.143)	(0.141)	(0.171)
Television X	-0.097	0.176	0.981**	0.188*
	(0.139)	(0.184)	(0.405)	(0.099)
Panel B: Results of LPG with interaction variables				
	Model 5	Model 6	Model 7	Model 8
Television	1.429***	1.425***	1.433***	1.332***
	(0.178)	(0.178)	(0.176)	(0.200)
Television X	-0.027	0.196	0.350	0.227**
	(0.138)	(0.187)	(0.384)	(0.096)
Panel C: Results of electricity with interaction variables				
	Model 9	Model 10	Model 11	Model 12
Television	1.119***	1.070***	1.152***	1.133***
	(0.303)	(0.300)	(0.294)	(0.347)
Television X	-0.152	-0.462*	6.591***	-0.136
	(0.192)	(0.240)	(0.345)	(0.135)
Panel D: Results of firewood with interaction variables				
	Model 13	Model 14	Model 15	Model 16
Television	-1.769***	-1.758***	-1.760***	-1.742***
	(0.088)	(0.087)	(0.086)	(0.103)
Television X	0.062	-0.031	-0.229	0.017
	(0.126)	(0.181)	(0.491)	(0.089)

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
In Panel A, the coefficient corresponding to "*Television* X" and the column *Primary* (or Model 1) is a coefficient for the interaction of *television* and *primary*; the coefficient corresponding to "*Television* X" and the column *Secondary* (or Model 2) is a coefficient of the interaction of *television* and *secondary*; the coefficient corresponding to "*Television* X" and the column *University* (or Model 3) is a coefficient of the interaction of *television* and *university*; and the coefficient corresponding to "*Television* X" and the column *Read* (or Model 4) is a coefficient of the interaction of *television a*nd the variable *read.* The same description also applies to the results reported in Panel B through Panel D. However, the coefficient of the variable *Television* is a coefficient of *Television* itself, not a coefficient of an interaction term.
Above results are estimated by controlling for all the variables used in Table 2. Full estimation results for each cooking fuel are reported in Appendix A1.

The result from the *LPG* model is comparable to that of the *clean fuel* model in terms of the sign and significance level of all variables. However, in the *electricity* model, the coefficients of the education variables and the variable *loan* are not significant. The variable *female* is also negative and not significant in the electricity model. The rest of the variables are also comparable to the clean fuel models. However, the variable of interest, television, is still positive and significant in both the *LPG* and *electricity* models. In the *firewood* model, as expected, the coefficient of *television* is negative and significant at the 1 percent level, indicating that households are less likely to adopt *firewood* when they are better informed. Other variables such as *electrified*, *age*, *loan*, *secondary* and *university* are negative, as expected, indicating that households that have access to the electricity grid and more educated households are less likely to use *firewood*. However, the variables *age* and *market* are positive, indicating that households headed by the elderly are more likely to use *firewood*.

The sensitivity of the coefficient of the variable *television* is tested by adding the interaction variables with *television* and the educational level (*primary, secondary* and *university*) for the *LPG, electricity* and *firewood* models, as reported in Table 3, Panel B through Panel D, respectively. The bivariate probit model of each fuel is estimated by including the interaction variables of *television* and the education variables. The coefficient of television is still significant at a conventional level in all models (*LPG, electricity* and *firewood,* as reported in Table 3, Panel B through Panel D). Thus, the coefficient of *television* is significant and robust in the checks that we performed above.

5.4 Policy Discussion: The Effect of Information

The results show that information disseminated through *television* has a positive effect on the adoption of *clean fuel* for cooking, and the results are robust to different specifications tests that we performed above. The average partial effects (APEs) of the variable television for all the models are reported in Table 4. The results show that households exposed to information disseminated through *television* are 41 percent more likely to adopt *clean fuel*, and this result is significant at the 1 percent level. We also report the APE for each fuel: *LPG*, *electricity* and *firewood*. Our results show that households are approximately 42 and 17 percent more likely to adopt LPG and electricity, respectively, and that households are approximately 49 percent less likely to adopt firewood when they have access to information through television. In our estimation results, we suspect that households that have a high preference for technology may also have a high preference for both clean fuel and television. Despite having accounted for such endogeneity issues econometrically, we still suspect that our model has overestimated the effect of information. In view of this shortcoming, we interpret our results as an upper bound partial effect. Despite the above shortcomings, educational programs and promoting clean fuel via *television* may be helpful in adopting *clean fuel* in areas of wide television coverage.

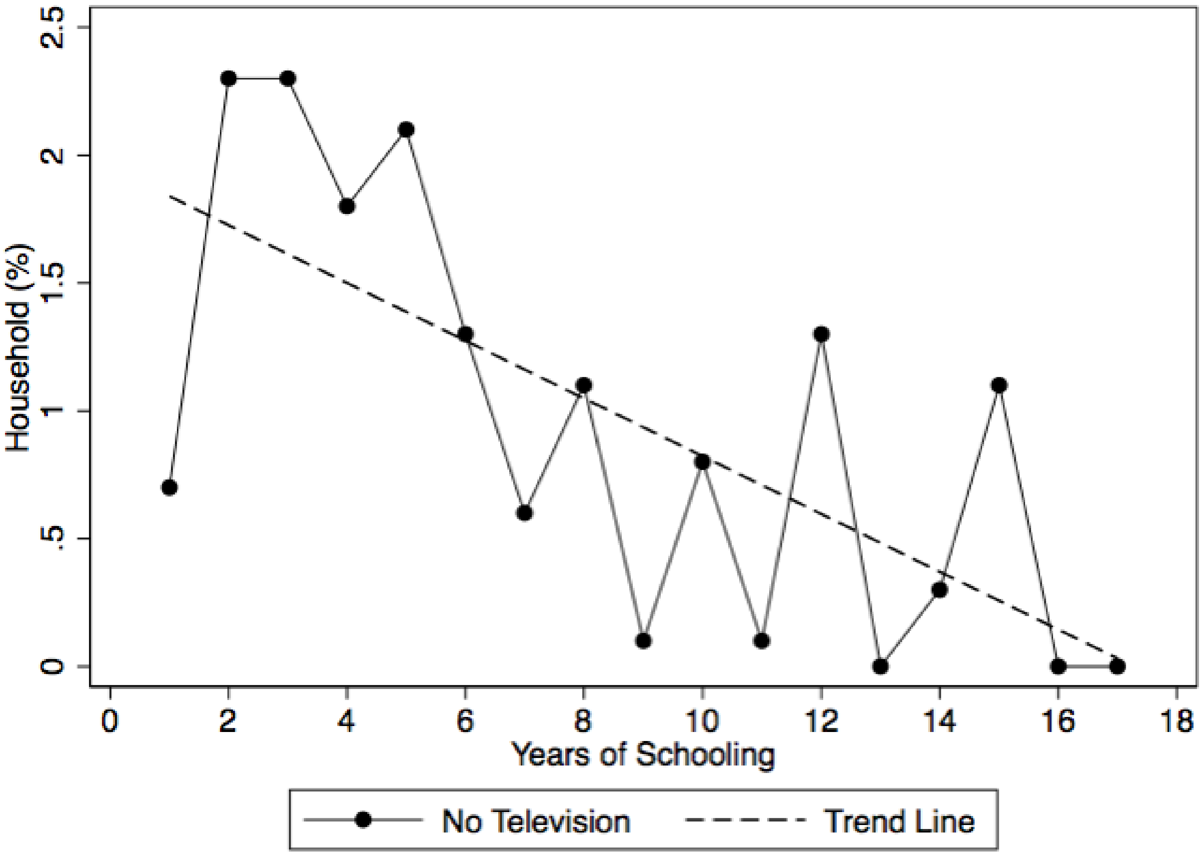
Table 4
Average Partial Effect of Television

Variables	APE of Television
Clean fuel	0.407***(0.049)
LPG	0.416***(0.063)
Electricity	0.167*(0.091)
Firewood	-0.494***(0.031)

*** p<0.01, ** p<0.05, * p<0.1; Standard errors in parenthesis are estimated from 500 bootstrap samplings and the setting seed at 123 in Stata 14. The Stata program is included in Appendix A2.

However, while designing information programs aimed at promoting the adoption of *clean fuel* and related technology, it may be important to consider the level of education of the program recipients. The results show that the effect of information disseminated via *television* will vary between groups that have higher and lower levels of educational attainment, as well as those comprised of individuals who can read and write. As reported in Table 3, the *television* and *university* interaction variable is positive and significant. This result can be interpreted such that, in contrast to those who do not own a *television* and who have no formal educational training, households headed by those with *university* education and households that own a *television* are more likely to adopt clean cooking fuel. Simultaneously, the interaction variable with *television* and *primary* and *secondary* schooling is not significant, thus suggesting the importance of the need to understand the educational level of the information recipients. In our sample, only approximately 11, 9 and 4 percent of household heads reported having completed primary, secondary and university education, respectively. As a result, we suspect that the small variation in educational attainment is affecting the significance level of these two interaction variables. Similarly, the *television* and *read* interaction variable is significant, suggesting that if household heads can read and write, households are more likely to adopt clean cooking fuel. Thus, educational attainment and literacy ability may be some of the most important factors to consider when television programs are designed to promote clean cooking fuel in developing countries.

Figure 1
Declining “no television ownership” with higher years of schooling



Our data also shows that households headed by an individual with a lower level of education seem to have a lower rate of television adoption. As reported in Figure 1, as the level of education increases, the percentage of households without a television decreases. This result indicates that households headed by an individual with a lower level of education are also less likely to make an informed household decision. Therefore, the provision of information targeted to households headed by an individual with a lower level of education may be more effective.

6. Conclusion

This study has examined the effect of information (television ownership) on the adoption of clean cooking fuel, accounting for the potentially endogenous information variable *television* ownership. We also estimate the effect of information on three different fuels (*LPG*, *electricity* and *firewood*) separately. Our findings show that households that have access to information are approximately 41 percent more likely to adopt *clean fuel* for cooking. Similarly, households are 49 percent less likely to adopt dirty fuel (*firewood*) when exposed to information. Our results suggest that information disseminated through *television* is helpful in adopting *clean fuel*. The results are interpreted based on the plausible assumption that if households own a *television*, then they are more likely to have additional knowledge about environmental conservation, the health benefits of using *clean fuel* and the availability of alternative cooking fuels.

The results also show that the effect of information varies between educated and uneducated groups and between households headed by those who can read and write. This result suggests that when designing information programs such as awareness or educational programs aimed at promoting clean fuel or a similar technology, the variations in the level of education of the recipients may be an important factor to consider. Similarly, we find that households headed by an individual with a lower level of education are likely to have limited access to information; information targeted at this segment of society may be more effective. Our results also indicate that females show a stronger preference for clean cooking fuel. Finally, similar to many other studies, our study also provides evidence supporting the call to consider clean energy as a viable option for rural households in developing countries.

However, in our study, the types of television channels that households watch and the frequency with which television is watched are not controlled for since such information was not available in our dataset. In addition, authors are concerned with the fact that information can be easily shared with households that do not own a television by households that do. Due to the limitations of our data, such spillovers were also ignored in our analysis. In addition, we suspect that our model may have overestimated the effect of information on the adoption of clean fuel. We are uncertain whether the effect of information that we estimate is the true effect of information or captures the preference for technology. We interpret our results based on the above shortcomings. For future research, to disentangle the true effect of information on the adoption of clean cooking fuel, designing a field experiment in which information provision is randomly assigned to treatment and control households may be useful to capture the true effect of information.

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Appendix

Table A1
Bivariate Probit Results of Clean Fuel with Interaction Variables

Variables	Model 1 Clean Fuel	Model 2 Clean Fuel	Model 3 Clean Fuel	Model 4 Clean Fuel
Television	1.526***	1.509***	1.536***	1.386***
	(0.145)	(0.143)	(0.141)	(0.171)
TV X Primary	-0.097			
	(0.139)			
T V X Secondary		0.176		
		(0.184)		
TV X University			0.981**	
			(0.405)	
TV X Read				0.188*
				(0.099)
Primary	0.282***	0.241***	0.238***	
	(0.095)	(0.078)	(0.078)	
Secondary	0.313***	0.205	0.302***	
	(0.115)	(0.170)	(0.114)	
University	1.002***	0.998***	0.557**	
	(0.181)	(0.180)	(0.235)	
Read				0.265***
				(0.079)
Electrified	1.541***	1.529***	1.521***	1.568***
	(0.154)	(0.152)	(0.152)	(0.155)
Age	0.001	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.143***	0.141***	0.141***	0.179***
	(0.053)	(0.053)	(0.053)	(0.055)
Children	-0.004	-0.006	-0.008	0.002
	(0.054)	(0.054)	(0.054)	(0.054)
Size	-0.048***	-0.048***	-0.049***	-0.053***
	(0.012)	(0.012)	(0.012)	(0.012)
Loan	0.273***	0.271***	0.267***	0.305***
	(0.060)	(0.060)	(0.060)	(0.062)
Expenditure (*ln*)	-0.032	-0.032	-0.031	-0.030
	(0.022)	(0.022)	(0.021)	(0.022)
Market (*ln*)	-0.151***	-0.150***	-0.148***	-0.165***
	(0.021)	(0.021)	(0.021)	(0.023)
Forest (*ln*)	0.007	0.008	0.008	0.009
	(0.030)	(0.030)	(0.030)	(0.030)
Constant	-1.636***	-1.616***	-1.630***	-1.680***
	(0.246)	(0.246)	(0.245)	(0.252)
Observations	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes
ρ	-0.537***	-0.546***	-0.574***	-0.455***
	(0.122)	(0.122)	(0.125)	(0.131)
Loglikelihood	-4091	-4091	-4088	-4162

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The variable “TV X Primary” is the interaction of *television* and *primary*; “TV X Secondary” is the interaction of *television* and *secondary*; and “TV X University” is the interaction of *television* and *university*.
The results from the television equation are not reported; however, the results are the same across all models, as reported in Table 2.

Table A2
Results of the Probit, Bivariate Probit and Control Function Methods

	Probit	Bivariate Probit	Control Function		
Variables	Clean Fuel	Clean Fuel	Clean Fuel	Clean Fuel	Clean Fuel
Television	0.745***	1.506***	5.086***	4.731***	4.707***
	(0.052)	(0.145)	(1.010)	(1.048)	(1.038)
Electrified	1.831***	1.543***	1.038***	1.141***	1.121***
	(0.144)	(0.154)	(0.240)	(0.244)	(0.240)
Primary	0.306***	0.242***	0.112	0.130	0.128
	(0.079)	(0.078)	(0.094)	(0.095)	(0.095)
Secondary	0.593***	0.320***	-0.390	-0.321	-0.311
	(0.098)	(0.114)	(0.249)	(0.261)	(0.259)
University	1.419***	1.009***	0.081	0.209	0.217
	(0.179)	(0.181)	(0.343)	(0.360)	(0.356)
Age	0.000	0.000	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.171***	0.143***	0.103*	0.105*	0.103*
	(0.055)	(0.053)	(0.060)	(0.060)	(0.060)
Children	0.010	-0.005	-0.053	-0.045	-0.044
	(0.057)	(0.054)	(0.058)	(0.059)	(0.059)
Size	-0.039***	-0.048***	-0.090***	-0.086***	-0.086***
	(0.013)	(0.012)	(0.018)	(0.018)	(0.018)
Loan	0.383***	0.275***	0.033	0.071	0.070
	(0.057)	(0.060)	(0.097)	(0.102)	(0.101)
Expenditure (*ln*)	-0.041*	-0.032	-0.011	-0.014	-0.014
	(0.022)	(0.022)	(0.025)	(0.025)	(0.025)
Market (*ln*)	-0.193***	-0.152***	-0.070*	-0.082**	-0.081**
	(0.020)	(0.021)	(0.036)	(0.037)	(0.036)
Forest (*ln*)	0.007	0.007	0.012	0.014	0.015
	(0.029)	(0.030)	(0.029)	(0.029)	(0.029)
Residuals			-1.810***	-1.435***	-1.623***
			(0.420)	(0.469)	(0.435)
Television X Residuals				-0.399**	
				(0.166)	
Residuals Squared					-0.090***
					(0.034)
Constant	-1.459***	-1.633***	-2.949***	-2.630***	-2.691***
	(0.260)	(0.246)	(0.426)	(0.469)	(0.455)
Observations	4349	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes	Yes
Loglikelihood	-1770	-4092	-1760	-1757	-1756
Rho		-0.530***			
		(0.122)			

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Standard errors for the control function method are estimated from 500 bootstrap samplings by setting seeds at 1234.
The results from the television equation are not reported in the above bivariate probit model since they are reported in Table 2.

Table A3
Bivariate Probit Results of LPG with Interaction Variables

Variables	Model 5 LPG	Model 6 LPG	Model 7 LPG	Model 8 LPG
Television	1.429***	1.425***	1.433***	1.332***
	(0.178)	(0.178)	(0.176)	(0.200)
TV X Primary	-0.027			
	(0.138)			
TV X Secondary		0.196		
		(0.187)		
TV X University			0.350	
			(0.384)	
TV X Read				0.227**
				(0.096)
Primary	0.287***	0.276***	0.275***	
	(0.091)	(0.076)	(0.076)	
Secondary	0.445***	0.332*	0.441***	
	(0.122)	(0.174)	(0.122)	
University	1.247***	1.239***	1.095***	
	(0.217)	(0.218)	(0.269)	
Read				0.271***
				(0.076)
Electrified	0.601***	0.592***	0.596***	0.596***
	(0.092)	(0.092)	(0.092)	(0.094)
Age	0.000	0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Female	0.130**	0.128**	0.129**	0.157***
	(0.052)	(0.052)	(0.052)	(0.053)
Children	-0.001	-0.002	-0.002	0.007
	(0.052)	(0.052)	(0.052)	(0.052)
Size	-0.040***	-0.040***	-0.040***	-0.046***
	(0.012)	(0.012)	(0.012)	(0.012)
Loan	0.297***	0.294***	0.296***	0.325***
	(0.062)	(0.062)	(0.062)	(0.065)
Expenditure (*ln*)	-0.011	-0.011	-0.011	-0.006
	(0.021)	(0.021)	(0.021)	(0.021)
Market (*ln*)	-0.145***	-0.144***	-0.144***	-0.155***
	(0.021)	(0.021)	(0.021)	(0.022)
Forest (*ln*)	0.005	0.006	0.005	0.008
	(0.029)	(0.029)	(0.029)	(0.029)
Constant	-0.392	-0.382	-0.392	-0.390
	(0.248)	(0.248)	(0.248)	(0.259)
Observations	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes
ρ	-0.530***	-0.544***	-0.541***	-0.483***
	(0.146)	(0.150)	(0.148)	(0.155)
Loglikelihood	-4245	-4245	-4245	-4327

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The variable “TV X Primary” is the interaction of *television* and *primary*; “TV X Secondary” is the interaction of *television* and *secondary*; and “TV X University” is the interaction of *television* and *university*.
The results from the television equation are not reported; however, the results are the same across all models, as reported in Table 2.

Table A4
Bivariate Probit Results of Electricity with Interaction Variables

Variables	Model 9 Electricity	Model 10 Electricity	Model 11 Electricity	Model 12 Electricity
Television	1.119***	1.070***	1.152***	1.133***
	(0.303)	(0.300)	(0.294)	(0.347)
TV X Primary	-0.152			
	(0.192)			
TV X Secondary		-0.462*		
		(0.240)		
TV X University			6.591***	
			(0.345)	
TV X Read				-0.136
				(0.135)
Primary	0.097	0.059	0.051	
	(0.111)	(0.098)	(0.097)	
Secondary	-0.123	0.166	-0.129	
	(0.166)	(0.220)	(0.162)	
University	0.120	0.148	-0.484*	
	(0.250)	(0.251)	(0.278)	
Read				0.074
				(0.094)
Electrified	2.326***	2.364***	2.294***	2.330***
	(0.161)	(0.155)	(0.167)	(0.180)
Age	-0.005**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.023	-0.019	-0.025	-0.013
	(0.065)	(0.066)	(0.065)	(0.066)
Children	0.020	0.019	0.011	0.014
	(0.066)	(0.066)	(0.066)	(0.067)
Size	-0.036**	-0.034**	-0.036**	-0.034**
	(0.015)	(0.015)	(0.015)	(0.014)
Loan	0.087	0.098	0.077	0.085
	(0.081)	(0.081)	(0.082)	(0.087)
Expenditure (*ln*)	-0.051**	-0.051*	-0.049*	-0.051**
	(0.026)	(0.026)	(0.026)	(0.026)
Market (*ln*)	-0.108***	-0.112***	-0.105***	-0.106***
	(0.029)	(0.029)	(0.030)	(0.033)
Forest (*ln*)	-0.047	-0.048	-0.045	-0.048
	(0.036)	(0.036)	(0.036)	(0.036)
Constant	-1.183***	-1.192***	-1.206***	-1.230***
	(0.287)	(0.288)	(0.285)	(0.292)
Observations	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes
_	-0.406*	-0.358*	-0.468**	-0.396
	(0.216)	(0.207)	(0.223)	(0.247)
Loglikelihood	-3492	-3491	-3486	-3543

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The variable "TV X Primary" is the interaction of *television* and *primary*; "TV X Secondary" is the interaction of *television* and *secondary*; and "TV X University" is the interaction of *television* and *university*.
The results from the television equation are not reported; however, the results are the same across all models, as reported in Table 2.

Table A5
Bivariate Probit Results of Firewood with Interaction Variables

Variables	Model 13 Firewood	Model 14 Firewood	Model 15 Firewood	Model 16 Firewood
Television	-1.769***	-1.758***	-1.760***	-1.742***
	(0.088)	(0.087)	(0.086)	(0.103)
TV X Primary	0.062			
	(0.126)			
TV X Secondary		-0.031		
		(0.181)		
TV X University			-0.229	
			(0.491)	
TV X Read				0.017
				(0.089)
Primary	-0.117	-0.094	-0.094	
	(0.086)	(0.072)	(0.072)	
Secondary	-0.201*	-0.187	-0.203*	
	(0.106)	(0.151)	(0.106)	
University	-1.092***	-1.094***	-1.003***	
	(0.231)	(0.231)	(0.259)	
Read				-0.184***
				(0.066)
Electrified	-1.093***	-1.093***	-1.090***	-1.088***
	(0.105)	(0.106)	(0.105)	(0.106)
Age	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Female	-0.023	-0.023	-0.023	-0.043
	(0.050)	(0.050)	(0.050)	(0.052)
Children	0.003	0.004	0.004	-0.002
	(0.051)	(0.051)	(0.051)	(0.051)
Size	0.080***	0.080***	0.080***	0.086***
	(0.012)	(0.012)	(0.012)	(0.012)
Loan	-0.109*	-0.109*	-0.109*	-0.130**
	(0.056)	(0.056)	(0.056)	(0.057)
Expenditure (*ln*)	0.099***	0.099***	0.098***	0.098***
	(0.020)	(0.020)	(0.020)	(0.021)
Market (*ln*)	0.095***	0.095***	0.095***	0.104***
	(0.018)	(0.018)	(0.018)	(0.019)
Forest (*ln*)	-0.003	-0.003	-0.003	-0.005
	(0.028)	(0.028)	(0.028)	(0.028)
Constant	0.353	0.349	0.350	0.319
	(0.226)	(0.227)	(0.226)	(0.235)
Observations	4349	4349	4349	4349
District Dummy	Yes	Yes	Yes	Yes
_	0.927***	0.926***	0.930***	0.840***
	(0.123)	(0.122)	(0.123)	(0.125)
Loglikelihood	-4151	-4151	-4151	-4235

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
The variable "TV X Primary" is the interaction of *television* and *primary*; "TV X Secondary" is the interaction of *television* and *secondary*; and "TV X University" is the interaction of *television* and *university*.
The results from the television equation are not reported; however, the results are the same across all models, as reported in Table 2.