Household cooking technologies and REDD+:

Pilot experiences in Tanzania and across the tropics

by

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Abstract

Conserving forests and increasing energy efficiency are two key ways that developing regions can contribute to climate change mitigation. We examine whether and how initiatives to reduce emissions from deforestation and forest degradation (REDD+) affect household choice of cooking technology. We draw our evidence from household surveys in and around pilot REDD+ initiatives across the tropics, including two in Tanzania that promoted improved cookstoves as a way to reduce forest degradation. After controlling for confounding variables through propensity score matching and endogenous treatment-regression models, we find that the interventions in Tanzania did increase adoption of improved cookstoves, although the vast majority of households still cook on traditional three-stone fires. Across the tropics, we find that interventions to reduce deforestation and forest degradation are effective at encouraging LPG adoption, but interventions implemented in the context of REDD+ are not any more effective.

1. Introduction

Approximately 2.5 billion people worldwide rely on biomass as their primary energy source for cooking and heating (IEA, 2006). This widespread use has important implications for health and wellbeing, forest ecosystems, and carbon emissions. Indoor air pollution from cooking with biomass results in approximately 1.3 million premature deaths each year with the burden mainly falling on women and children (IEA, 2006). While wood is a renewable resource, unsustainable fuelwood extraction contributes to forest degradation and results in net greenhouse-gas (GHG) emissions (Hofstad et al., 2009; Weatherley-Singh & Gupta, 2015).

REDD was developed under the United Nations Framework Convention on Climate Change (UNFCCC) as a mechanism to reduce carbon emissions from deforestation and forest degradation in developing countries by financially compensating participants for moving away from activities that deplete and degrade the forest (United Nations, 2016). In 2007, the parties to the UNFCCC called for REDD demonstration activities. In 2009, conservation, sustainable forest management, and forest enhancement goals were added to the scope ("REDD+") (Pistorius, 2012), and in 2010, social safeguards were adopted (Jagger et al., 2014). Over the past decade, governments, civil society, and private business have launched initiatives to demonstrate REDD+ and in some cases, generate offset credits for the voluntary market (Luttrell et al. 2017). Sub-national REDD+ initiatives seek to reduce deforestation and forest degradation in a geographically defined region, often with a bundle of interventions ranging from education to direct conditional payments.

While promoting more efficient technology or more modern fuels for cooking is not the primary goal of REDD+, some initiatives have adopted this as part of their strategy to reduce forest degradation (e.g. in Tanzania, Sills et al. 2014). It is also possible that REDD+ interventions could indirectly or unintentionally affect household cooking decisions. For example, households may use additional income from conditional payments for REDD+ to purchase an improved cookstove (ICS) or more modern fuels. Increased enforcement of restrictions on forest access could encourage households to reduce fuelwood collection, while support for alternative livelihoods may make alternative technologies and fuels more accessible and provide additional income streams (Atela et al., 2015; Kessy et al., 2016; Pattanayak et al., 2004; Sills et al., 2003; Weber et al., 2011). REDD+ initiatives typically include an educational component designed to raise awareness about the negative consequences of deforestation and degradation, and this could also discourage fuelwood collection (Kessy et al., 2016). In addition, REDD+ proponents often seek to engage local communities in forest governance, which could reinforce these effects (Tacconi et al., 2013).

Given that energy and land use are two of the major contributors to GHG emissions, it is important to assess whether and how REDD+ influences household energy decisions. Combining global warming concerns with the fact that cooking with wood on a three-stone fire can cause premature mortality and high morbidity, any contribution of REDD+ towards replacing three-stone fires with improved cooking technology is important from the perspective of social safeguards (Jeuland & Pattanayak, 2012). With this motivation, we evaluate whether REDD+ pilot initiatives have affected choices about cooking technology by households initially reliant on three-stone fires. The effectiveness of a REDD+ initiative depends on two factors: the level of participation of households in the REDD+ interventions, and the impact of those interventions conditional on participation. Thus, it is relevant to assess both the effect of implementing a REDD+ initiative in a village (regardless of intervention participation rates) as well as the effect of participation in a REDD+ intervention. Furthermore, REDD+ initiatives are often implemented in regions where there are other conservation and sustainable development initiatives with similar types of interventions to reduce deforestation and forest degradation (Lin et al., 2012). As with many efforts to conserve tropical forests and improve local livelihoods, careful evaluations that account for selection of project sites and participations of household is rare, including in the case of REDD+ (Ferraro et al., 2011).

Thus, we ask the following research questions:

1. How does the presence of a REDD+ initiative in a village affect household choice of cooking technology?
2. What household characteristics predict participation in interventions to reduce deforestation and forest degradation?
3. Do these interventions have different effects on household energy choices depending on whether they are implemented in the context of REDD+?
4. Do REDD+ initiatives or interventions to reduce deforestation and forest degradation have different effects on the household energy choices of low income households as compared to middle- and high-income households?

While it would be reasonable to hypothesize that the answers depend on the specific interventions and context, we seek a general answer by analyzing data from sixteen REDD+ initiatives in six countries collected by CIFOR's Global Comparative Study (GCS) on REDD+ (Sills et al., 2014). The GCS sample includes both villages in REDD+ intervention areas and matched comparison villages outside those intervention areas. In each village, there was a baseline household survey (before the REDD+ intervention) and a second phase survey (2-3 years later). These surveys elicited information on household participation in interventions intended to reduce deforestation and forest degradation, as implemented by the REDD+ proponent or other organizations. This allows us to (a) assess both the impact of residing in the REDD+ intervention area as well as the impact of directly participating in an intervention, and (b) compare the impact of forest conservation interventions implemented in the context of REDD+ and where there is no REDD+ initiative.

Careful appraisal is needed because REDD+ is typically implemented where international and local NGOs are active and often implement their mixed brand of conservation efforts such as conditional and non-conditional livelihood promotion strategies and environmental education (Lin et al., 2012; Sunderlin et al., 2010). The presence of these international and regional NGO players creates a clouded landscape in terms of REDD+ additionality. Thus, we primarily rely on a triple-difference regression strategy to estimate the extent of this additionality. We hypothesize that REDD+ may increase the effectiveness of interventions because of requirements such as monitoring, reporting, and verification (as a basis for conditionality) and free prior informed consent (as a way to obtain community buy-in), and may lead to greater benefits for the poor (because of the emphasis on equity and social safeguards in REDD+).

In order to address our research questions, we need to understand the counterfactual: what would households have chosen for cooking technology if they or their village had not participated in a REDD+ initiative or specific intervention (Pattanayak, 2009)? Although there was a long history of "avoided deforestation" initiatives even before the launch of REDD+, they had rarely been rigorously evaluated and almost never evaluated using a consistent counterfactual to evaluate impacts in different domains (Caplow et al., 2011). An evidence base on REDD+ is now slowly emerging, with a few ex post evaluations, e.g. in Nepal and Brazil (Fischer et al., 2016; Sharma et al., 2015; Simonet et al., 2015). We contribute to this literature by evaluating the impact of REDD+ initiatives in the pan-tropical GCS sample, as well as the impact of two specific interventions in Tanzania that promoted household energy transitions as a way to reduce forest degradation.

2. Methods

2.1 Data Collection

CIFOR launched the GCS in 2009 with the aim of understanding the enabling conditions and challenges for REDD+ (Sills et al., 2014). One component of the GCS seeks to learn lessons from the subnational initiatives launched as demonstration activities called for by the UNFCCC, as well as to generate carbon offsets for the voluntary market. This component included data collection in multiple phases between 2009 and 2013, including household surveys in 16 subnational initiatives in six countries: Brazil, Peru, Cameroon, Tanzania, Indonesia, and Vietnam (Figure 1). These countries were selected to represent varying stages of and responses to deforestation transitions across three main continents and are representative of the global population of REDD+ pilot initiatives (Sills et al., 2014).

CIFOR selected subnational initiatives that had not yet offered conditional incentives at the start of data collection. However, these initiatives were not located in space at random – i.e., there is deliberate non-random site selection (Lin et al., 2012). Therefore, for each initiative, pre-matching was used to select four intervention and four control villages for inclusion in the survey (Sunderlin et al., 2010). These villages were selected to obtain a balanced sample on a set of 22 characteristics related to markets, sociodemographics, and land use. Furthermore, control villages were only selected if they were sufficiently far enough away from REDD+ villages to avoid issues with spillover and leakage (Sills et al., 2014). Field teams sought to interview 30 households within each control and treatment village, selected via simple random sampling, resulting in a minimum of 240 households in all sites except two. In each selected household, the household head was interviewed about household characteristics, production, and forest use. From this sampling procedure, we have 4,643 unique households in the final sample.

Figure 1. GCS study sites where household survey was conducted

Across these 16 sites, 207 unique interventions were recorded and they are grouped into seven broad categories: (1) Restriction on forest access and conversion, (2) non-conditional livelihood enhancement, (3) conditional livelihood enhancement, (4) environmental education, (5) forest enhancement, (6) tenure clarification, and (7) other (e.g. fire management, village development planning, forest inventory measurement). We include all intervention categories in our intent-to-treat analysis of how the presence of a REDD+ initiative in a village affects household choice of cooking technology (research question 1). For research questions 2-4, we define a household as participating in an intervention intended to reduce deforestation only if they participated in categories (1)-(4), as these include the interventions most likely to affect household energy choices.

We analyze the impact of REDD+ on household energy transitions, both using the pan-tropical sample and focusing on the two initiatives in Tanzania (Figure 2), as these were the only ones that targeted household energy transitions, e.g. by promoting and providing training on improved fuelwood-efficient stoves. The full names of these two initiatives are the Community Based REDD Mechanisms for Sustainable Forest Management in Semi-Arid Areas (located in the Shinyanga region), and Making REDD work for Communities and Forest Conservation in Tanzania (located in Kilosa, in the Morogoro region). Both are described in detail in Sills et al. (2014).

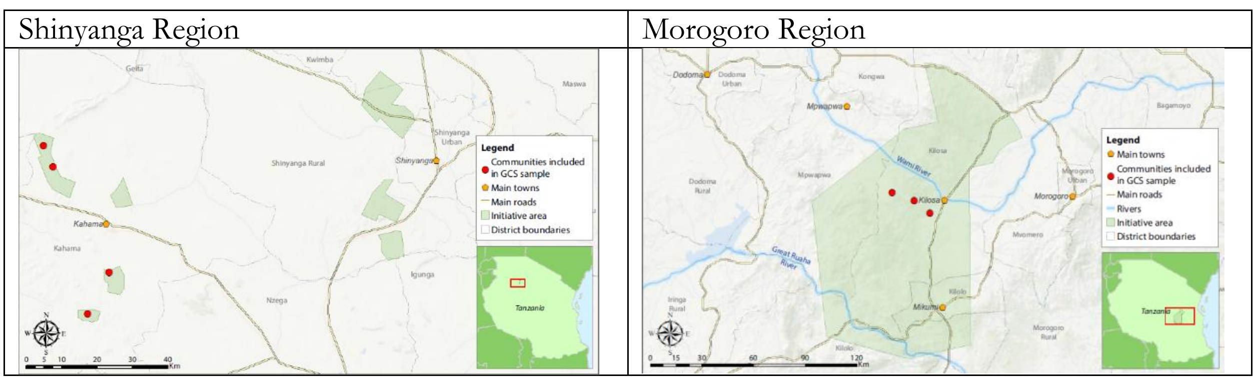

Figure 2. GCS in Tanzania

The survey asked respondents to name the main type of cooking fuel used by the household. Based on their answers, we consider four binary outcomes indicating whether the household primarily cooks with (1) fuelwood, (2) a three-stone fire, (3) an improved fuelwood cookstove, and (4) LPG. All households that cook with fuelwood primarily use either a three-stone fire or an improved fuelwood cookstove. Both options (3) and (4) may reduce the quantity of fuelwood consumed and improve the air quality around the cooking area. Note that only primary fuels and primary cooking technologies are reported, rather than all fuels and technologies used by the household. Thus, the three-stone fire and improved fuelwood cookstove outcomes do not overlap with the LPG outcome.

2.2 Statistical Models

We estimate the impacts of REDD+ using quasi-experimental econometric techniques. Difference-in-difference (DID) and triple-difference (DDD) models are the primary mechanisms used to recover impact estimates. In addition, because not all households within a village with a REDD+ initiative participated in the interventions, we also implement intent-to-treat analysis, propensity score matching, and endogenous treatment regression models to address endogeneity of households' decisions to participate in the interventions. While the intent-to-treat estimate reflects impacts on both intervention participants and non-participants in REDD+ villages, propensity score matching and the endogenous treatment model are used to estimate the localized impacts of REDD+ conditional on participation in at least one intervention.

We focus attention on the households who were initially cooking over three-stone fires, as they were likely the poorest households in the REDD+ intervention areas. Specifically, we restrict our sample for the regression analyses to households using three-stone fires as their primary energy source in the baseline. For the ICS and LPG outcomes, a value of 1 indicates that a household was using a three-stone fire in the baseline but has adopted the cleaner fuel/cooking technology in the second phase. For the fuelwood and three-stone fire outcomes, a value of 1 indicates that households were using three-stone fire in the baseline but had adopted a different fuel/technology in the second phase. A positive coefficient on REDD+ therefore always indicates that it encouraged households to use cleaner fuels or technologies.

2.2.1 Intent to treat analysis

We first estimate the intent to treat (ITT) effect of REDD+ at the village-level. The ITT analysis estimates the effect of living in a REDD+ intervention area on household energy outcomes, regardless of whether or not that household participated in an intervention. We estimate the ITT effect (β_1) with the following DID model:

$$(1) \quad (Y_{i,t} - Y_{i,t-1}) = \beta_0 + \beta_1 REDD_i + (\varepsilon_{i,t}\text{-}\varepsilon_{i,t-1})$$

Where:

$$\text{REDD}_i = \begin{cases} 1, \text{ household located in a village implementing any REDD+intervention} \\ 0, \text{ household located in a control village with no REDD+interventions} \end{cases}$$

$(Y_{i,t} - Y_{i,t-1})$ = change in household energy outcome of household *i* between survey phases

We further cluster standard errors at the village level to account for relationships in unobserved variables among households within the same village.

2.2.2 Propensity score matching

Two types of potential selection bias could affect our statistical models. First, REDD+ proponents do not randomly implement REDD+ programs in villages and households, but likely target them based on dimensions such as deforestation threats, strength of local institutions, and prior experience with conservation NGOs. If factors influencing the selection of villages and households into REDD+ also influence household energy outcomes, simple comparison will produce a biased estimate of the treatment effect. To address this selection of villages into REDD+, pre-matching techniques were used to select a balanced sample of villages for the survey (Sills et al., 2017).

Second, self-selection of households into intervention participation was addressed by implementing nearest-neighbor propensity score matching (with replacement) at the household level, using household survey data on the covariates listed in Table A- 1. We exclude 106 treatment households not on common support and 617 control households without a nearest-neighbor match. We further drop observations from the sample that either did not complete both phases of the survey (1,114 households), moved villages between phases (31 households), or were missing data on intervention participation (507 households) to obtain a final matched sample of 2,377 households. As shown in Table A- 1, the sample is well balanced on most variables, except for two variables indicating whether the household head was born in the village and low quality housing materials. We therefore include controls for these two indicator variables in our post-matching regressions. Other time-invariant variables that are unobserved and may remain unbalanced are swept out by Triple Difference (DDD) estimation.

Table 1. Sample Description

Country	REDD+ Village		Control Village		Total Households
	Intervention Participation	Did Not Participate	Intervention Participation	Did Not Participate	
Brazil	430 (29)	45 (4)	279 (12)	32 (6)	**786 (51)**
Peru	141 (88)	14 (13)	107 (73)	23 (19)	**285 (193)**
Cameroon	189 (184)	10 (10)	119 (110)	45 (41)	**363 (345)**
Tanzania	103 (102)	47 (46)	18 (18)	50 (49)	**218 (215)**
Indonesia	309 (178)	145 (118)	21 (11)	114 (74)	**589 (381)**
Vietnam	44 (42)	42 (39)	25 (25)	25 (23)	**136 (129)**
Total	**1,216 (623)**	**303 (230)**	**569 (249)**	**289 (212)**	**2,377 (1,314)**

Number of households using three-stone fires at baseline in parentheses

An important feature of the GCS data is that even in control villages, there were interventions intended to reduce deforestation and forest degradation implemented by organizations not affiliated with any REDD+ initiative (Table 1). In the larger pan-tropical sample, this allows us to evaluate the moderating effect of REDD+ (e.g. due to requirements imposed by safeguards and conditionality) on the effectiveness of interventions to reduce deforestation and forest degradation, by estimating the following DDD model:

$$(2)\ \left(Y_{i,t} - Y_{i,t-1}\right) = \beta_0 + \beta_1 Interv_i + \beta_2 REDD_i + \beta_3 (Interv \cdot REDD)_i + \beta_4 HHBorn_i + \beta_5 PoorHousing_{i,t-1} + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$$

Where:

$$REDD_i = \begin{cases} 1, \text{ household located in a village implementing any REDD+intervention} \\ 0, \text{ household located in a control village with no REDD+interventions} \end{cases}$$

$$Interv_i = \begin{cases} 1, \text{ household participated in an interventions expected to affect fuelwood harvest}^1 \\ 0, \text{ household did not participate in any intervention expected to affect fuelwood harvest} \end{cases}$$

$HHBorn_i$ = Household head born in village

$PoorHousing_{i,t-1}$ = Home constructed from low quality materials (at baseline)

[1] Defined as participation in (1) restriction on forest access and conversion, (2) non-conditional livelihood enhancement, (3) conditional livelihood enhancement, and/or (4) environmental education

$(Y_{i,t} - Y_{i,t-1})$ is the change in household energy outcome of household *i* between survey phases, and the coefficient β_3 is the added impact of REDD+ on a deforestation and forest degradation intervention, as compared to the same intervention implemented in a control village. Again, standard errors are clustered at the village level to account for relationships in unobserved variables among households within the same village. Because we are utilizing panel data rather than independent cross sections, we first-difference the data to avoid bias from the relationship in unobservables across time due to the same households being present in both phases of the study. As a result, there is no time variable in the model. Note that we are not able to estimate models using propensity score matching for the Tanzanian subsample due to insufficient variation.

2.2.3 Two-stage endogenous treatment model

As an alternative approach to addressing potential selection bias, we also estimate the DDD models using a modification of Heckman's two-step sample selection model, known as an endogenous treatment-regression model (Vella, 1998). This model is specified in equations (3) and (4) as detailed in Maddala (1986).

$$(3)\quad \left(Y_{i,t} - Y_{i,t-1}\right) = \beta_1 Interv_i + \beta_2 HHBorn_i + \beta_3 PoorHousing_{i,t-1} - u_1$$

$$(4)\quad Interv_i^* = \gamma_2' x_2 - u_2$$

Where: *Interv = 1 if Interv* > 0*
Interv = 0 if Interv ≤ 0*

And combining these equations yields equation (5):

$$(5)\quad E\left(\left(Y_{i,t} - Y_{i,t-1}\right) | Interv = 1\right)$$
$$= \beta_1 + \beta_2 HHBorn_i + \beta_3 PoorHousing_{i,t-1} - E(u_1 | u_2 < \gamma_2' x_2)$$
$$= \beta_1 + \beta_2 HHBorn_i + \beta_3 PoorHousing_{i,t-1} - \sigma_{12} \frac{\phi(\gamma_2' x_2)}{\Phi(\gamma_2' x_2)}$$

Where:

σ_{12} = cov(u_1,u_2)
ϕ = density function of standard normal at $\gamma_2' x_2$
Φ = distribution function of standard normal at $\gamma_2' x_2$

The error terms u_1 and u_2 are correlated due to shared unobservable factors influencing both intervention participation and household energy outcomes. The vector x_2 contains a series of characteristics explaining participation in an intervention. Using the two-stage estimate method we estimate $\hat{\gamma}_2$ for γ_2 using a probit maximum likelihood, then regress the change in household energy outcome on $\frac{\phi(\gamma_2' x_2)}{\Phi(\gamma_2' x_2)}$ and the household head birthplace and housing quality indicators.

2.2.4 Heterogeneous impacts on income

To address the possibility that REDD+ and other deforestation interventions affected lower income households differently than middle and high income households, we interact a low-income indicator with the REDD+ and intervention variables in the full-sample DDD models.

$$(7)\ \left(Y_{i,t} - Y_{i,t-1}\right) = \beta_0 + \beta_1 LowIncome_{i,t-1} + \beta_2 REDD_i + \beta_3 (LowIncome_{t-1} \cdot REDD)_i + \beta_4 HHBorn_i + \beta_5 PoorHousing_{i,t-1} + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$$

$$(8)\ \left(Y_{i,t} - Y_{i,t-1}\right) = \beta_0 + \beta_1 LowIncome_{i,t-1} + \beta_2 Interv_i + \beta_3 (LowIncome_{t-1} \cdot Interv)_i + \beta_4 HHBorn_i + \beta_5 PoorHousing_{i,t-1} + (\varepsilon_{i,t} - \varepsilon_{i,t-1})$$

The income indicator is constructed from baseline income terciles of each study site, as detailed in Ickowitz et al. (2017). Income terciles are defined based on total household income per adult equivalent. Thus, a household is defined as low income if they are in the lowest income tercile at their study site.

3. Results

Examining how households in the matched sample are transitioning between cooking technologies, we see substantial inertia in both Tanzania (Table 2) and the pan-tropical GCS sample (Table 3). In Tanzania, 95% of households in the sample use a three-stone fire in both phases of the study, with three-stone fire users who adopt an improved biomass stove comprising 4% of households and improved biomass stove users who switch to a three-stone fire comprising 1% of households. While fewer households rely on three-stone fires in the other GCS countries, we see a similar stickiness in choice of cooking technology, with 76% of households reporting that they use the same cooking technology in both phases. However, 19% adopt a cleaner cooking technology while only 4% shift to a dirtier technology. The largest single shift is the 10% of households using an improved biomass stove in the baseline who reported using LPG in the second phase.

Table 2. Transition Matrix of Cooking Technology for Households - Tanzania

	Technology	Before (Baseline)		
		Three-Stone Fire	Improved Stove	LPG
After	Three-Stone Fire	345 (95%)	4 (1%)	0 (0%)
	Improved Stove	13 (4%)	1 (0%)	0 (0%)
	LPG	0 (0%)	0 (0%)	0 (0%)

Number of households, with percentages in parentheses

Table 3. Transition Matrix of Cooking Technology for Households - All GCS Countries

	Technology	Before (Baseline)		
		Three-Stone Fire	Improved Stove	LPG
After	Three-Stone Fire	1,706 (53%)	110 (3%)	39 (1%)
	Improved Stove	45 (1%)	376 (12%)	15 (0%)
	LPG	263 (8%)	311 (10%)	341 (11%)

Number of households, with percentages in parentheses

3.1 Tanzania

As shown in Figure 3, over 98% of Tanzanian households used fuelwood, including 95% who used three-stone fires, for their cooking needs at baseline. While these percentages decline somewhat for households in REDD+ villages after intervention implementation, the vast majority do not adopt alternative fuels or cooking technologies. Figure 4 shows that while adoption of improved cookstoves increases substantially more in REDD+ villages than other villages in the second phase, the magnitude of improved stove use is still only approximately 6%. This is shown more clearly in the Appendix, where Tanzania has among the highest use rates of fuelwood and three-stone fires, lowest use rate of ICS rates, and negligible LPG use.

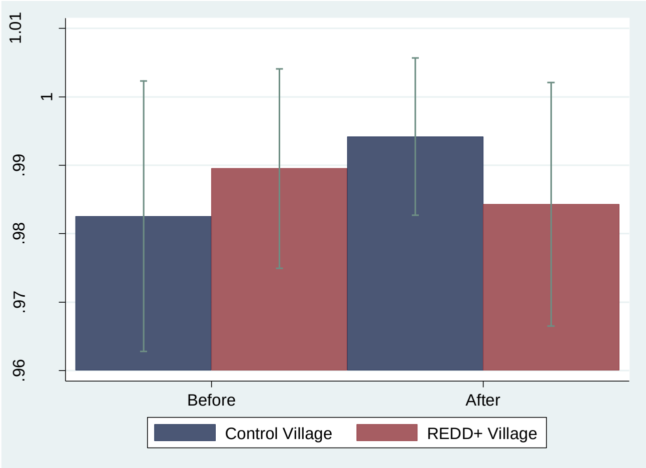

Figure 3. Tanzanian households using fuelwood (proportion and 95% CI)

Difference-in-differences regression results for Tanzania are presented in Table 4 for fuelwood outcomes and Table 5 for improved biomass stove outcomes. The first columns report the ITT effect of residing in a REDD+ village. The second columns report the average treatment effect of participating in a REDD+ or other deforestation intervention with no correction for self-selection bias, while the third column reports results of the endogenous treatment-regression model. We are not able to estimate models using propensity score matching for the Tanzanian subsample due to lack of common support. LPG outcomes are not presented because no households reported using LPG in either phase of the survey (see Table 2). Thus, three-stone fire outcomes are also not presented due to overlap with the fuelwood and three-stone fire outcomes. None of the estimated coefficients in Table 4 are statistically significant. Households do not appear to change their fuelwood use in response to either the presence of REDD+ in their village or their participation in a deforestation or forest degradation intervention.

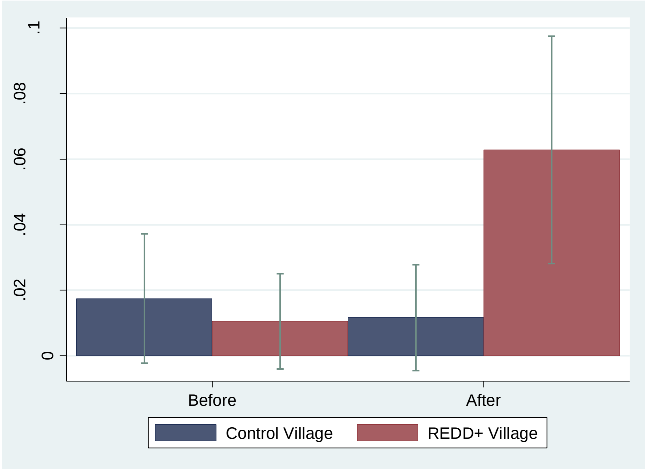

Figure 4. Tanzanian Households using an improved biomass stove (proportion and 95% CI)

Table 5 shows that living in a REDD+ village significantly increases the probability of using an improved cookstove in Tanzania by approximately 5.8 percent. However, participation in an intervention intended to decrease deforestation and forest degradation (including interventions inside and outside REDD+ intervention areas) does not influence improved cookstove use after correcting for self-selection bias. As targeted cookstove interventions were only available in REDD+ villages, these results provide support for the efficacy of targeted household energy interventions.

Table 4. DID Results – Fuelwood in Tanzania

Variable	(1) REDD+	(2) Intervention, Unadjusted [a]	(3) Intervention, ET [b]
REDD+ Village	0.0159		
	(0.0107)		
Intervention Participation		0.0108	0.0685
		(0.0157)	(0.0623)
Constant	-0**	0.00538	-0.0178
	(0)	(0.00539)	(0.0230)
Observations	357	310	305
R-squared	0.008	0.003	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Model not adjusted for endogeneity of intervention participation
[b] Endogenous treatment model, adjusting for endogeneity of intervention participation

Table 5. DID Results- Improved biomass stove use in Tanzania

Variable	(1) REDD+	(2) Intervention, Unadjusted [a]	(2) Intervention, ET [b]
REDD+ Village	0.0576**		
	(0.0260)		
Intervention Participation		0.0834*	0.0976
		(0.0457)	(0.0665)
Constant	0.00588	0.00535	-0.00330
	(0.00560)	(0.00536)	(0.0172)
Observations	358	311	306
R-squared	0.024	0.045	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Model not adjusted for endogeneity of intervention participation
[b] Endogenous treatment model, adjusting for endogeneity of intervention participation

3.2 Estimation Results with Full Sample

3.2.1 ITT results: How does the presence of a REDD+ initiative in a village affect household choice of cooking technology?

ITT analysis is relevant from a policy perspective because its effects incorporate both the impact of the intervention and the rates in which households participate in REDD+. Results of the ITT analysis are presented in Table 6. The presence of REDD+ in a village does not have a significant effect on any of the four household energy outcome variables. These results are perhaps not surprising, as households are participating in interventions targeting deforestation and forest degradation in both REDD+ and control villages. Thus, it does not appear that REDD+ is inducing households to shift to cleaner cooking technology at greater rates than villages not associated with REDD+.

Table 6. Intent to Treat Effects

Variable	(1) Fuelwood	(2) Three-stone fire	(3) Improved biomass stove	(4) LPG
REDD+ Village	-0.0166	-0.00734	0.00724	-0.0161
	(0.0339)	(0.0360)	(0.00983)	(0.0347)
Constant	0.148***	0.169***	0.0181***	0.137***
	(0.0260)	(0.0272)	(0.00563)	(0.0268)
Observations	2,038	2,044	2,044	2,044
R-squared	0.001	0.000	0.001	0.001

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

[a] Model not adjusted for endogeneity of intervention participation

[b] Endogenous treatment model, adjusting for endogeneity of intervention participation

3.2.2 First-stage results: What household characteristics predict participation in deforestation interventions?

Among REDD+ villages, approximately 71 percent of households participated in an intervention, while participation rates are lower in control villages at 55 percent. We estimate a probit model to identify the characteristics of households that are most associated with propensity to participate in deforestation interventions. Predictor variables fall into the broad categories of income and income sources, land ownership, household head characteristics, and household characteristics. Table 7 presents results of this estimation for both REDD+ and control villages.

Table 7. Intervention Participation Probit Model

Variable	(1) REDD+ Villages	(2) Control Villages
Log(income per adult equivalent)	0.0515	0.190***
	(0.0387)	(0.0536)
Log(total land)	0.321***	0.321***
	(0.0501)	(0.0521)
Insecure tenure	0.122	-0.0973
	(0.130)	(0.114)
Share of income from forest activities	0.822***	0.187
	(0.272)	(0.233)
Household cleared any forest	0.156	0.331**
	(0.111)	(0.131)
NGO support	0.175	-
	(0.400)	
Government support	-0.0867	-0.127
	(0.167)	(0.207)
Education	0.0188	-0.00126
	(0.0142)	(0.0162)
Household head male	-0.136	-0.151
	(0.129)	(0.130)
Age	-0.00429	-0.00298
	(0.00365)	(0.00426)
Household head ethnicity	-0.253	-0.150
	(0.179)	(0.187)
Household head born in village	0.0149	-0.308**
	(0.120)	(0.136)
Dependency ratio	0.0643	0.0993
	(0.0635)	(0.0646)
Poor housing quality	-0.0751	-0.131
	(0.112)	(0.120)
Constant	-0.411	-1.739***
	(0.425)	(0.563)
Observations	1,794	1,149

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

In both REDD+ and control villages, households that owned larger areas of land were more likely to participate in an intervention aimed at reducing deforestation and forest degradation. However, income is only a positive predictor of intervention participation in control villages, perhaps due to the emphasis on equity and social safeguards among REDD+ initiatives. Households with more forest activity were also more likely to participate. A ten percentage point increase in share of forest income is associated with an eight percent higher probability of participation in REDD+ villages, and households who cleared any forest in the past two years are 33 percent more likely to participate in control villages. These results are consistent with the idea that deforestation interventions are targeted at households with greater forest activity and may provide greater incentives for these households to participate.

3.2.3 Second-Stage Results: How do REDD+ initiatives and deforestation interventions influence household energy choices?

The DDD results for all countries in Table 8 show no additional effect of an intervention implemented in the context of REDD+ on the probability of shifting away from use of fuelwood or three-stone fire. However, intervention participation in either a REDD+ or non-REDD+ context is associated with a significant shift away from fuelwood use at a 10% significance level. As expected, households of lower socio-economic status, as indicated by their housing materials, are less likely to move up the energy ladder to new technologies or fuels for cooking.

Turning to the probability of adopting an ICS or LPG in Table 9, we similarly see that REDD+ does not increase the effectiveness of interventions in encouraging adoption of cleaner cooking fuels and technology. Intervention participation does significantly increase the probability that a household will shift from using a three-stone fire to LPG under the endogenous treatment model, but not the propensity score model. Our results suggest that while interventions targeting deforestation and forest degradation are effective in inducing shifts away from fuelwood and to LPG, REDD+ does not increase the effectiveness of those interventions.

Table 8. DDD Results– All Countries, Traditional Technology [a]

Variable	Fuelwood			3-Stone Fire		
	(1) Unmatched [b]	(2) PSM [c]	(3) ET [d]	(1) Unmatched [b]	(2) PSM [c]	(3) ET [d]
REDD+ village	0.0445 (0.0423)	0.0560 (0.0680)	0.0513 (0.0429)	0.0426 (0.0429)	0.0520 (0.0726)	0.0510 (0.0462)
Interv. participation	-0.0392 (0.0349)	-0.0745 (0.0483)	0.293* (0.173)	-0.0286 (0.0383)	-0.0714 (0.0486)	0.177 (0.311)
REDD+ village x Interv. participation	-0.0340 (0.0383)	-0.0358 (0.0654)	0.0382 (0.0372)	0.000367 (0.0436)	-0.0123 (0.0704)	0.0501 (0.0529)
HH head born in village	-0.0359* (0.0205)	-0.0557 (0.0364)	-0.0375 (0.0290)	-0.0427* (0.0218)	-0.0721* (0.0385)	-0.0436 (0.0266)
Poor housing condition	-0.0850*** (0.0212)	-0.0944*** (0.0301)	-0.0681** (0.0339)	-0.0734*** (0.0247)	-0.0822** (0.0317)	-0.0646* (0.0369)
Constant	0.183*** (0.0370)	0.213*** (0.0658)	-0.00858 (0.100)	0.192*** (0.0387)	0.236*** (0.0710)	0.0740 (0.186)
Observations	1,739	1,899	1,707	1,745	1,904	1,713
R-squared	0.028	0.047		0.018	0.035	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Estimates for households using three-stone fire in baseline
[b] Model not adjusted for endogeneity of intervention participation
[c] Propensity score matching model
[d] Endogenous treatment model

Table 9. DDD Results– All Countries, Cleaner Technology [a]

Variable	Improved Biomass Stove			LPG		
	(1) Unmatched [b]	(2) PSM [c]	(3) ET [d]	(1) Unmatched [b]	(2) PSM [c]	(3) ET [d]
REDD+ village	0.000898 (0.00677)	0.0122 (0.0148)	0.000173 (0.00714)	0.0378 (0.0426)	0.0223 (0.0708)	0.0387 (0.0394)
Interv. participation	0.00662 (0.00948)	0.00847 (0.00958)	-0.00842 (0.0769)	-0.0287 (0.0363)	-0.0782 (0.0487)	0.369*** (0.0515)
REDD+ village x Interv. participation	0.0289** (0.0145)	0.00946 (0.0216)	0.0204 (0.0144)	-0.0352 (0.0399)	-0.0175 (0.0666)	0.0253 (0.0371)
HH head born in village	-0.00465 (0.00729)	-0.0102 (0.00895)	-0.00397 (0.00666)	-0.0334* (0.0198)	-0.0537 (0.0370)	-0.0344 (0.0304)
Poor housing condition	0.0199** (0.00903)	0.0245* (0.0126)	0.0178* (0.00914)	-0.0905*** (0.0207)	-0.0933*** (0.0294)	-0.0696** (0.0346)
Constant	0.00240 (0.00661)	0.00178 (0.00687)	0.0116 (0.0437)	0.176*** (0.0374)	0.219*** (0.0704)	-0.0501 (0.0375)
Observations	1,745	1,904	1,713	1,745	1,904	1,713
R-squared	0.013	0.016		0.029	0.043	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Estimates for households using three-stone fire in baseline
[b] Model not adjusted for endogeneity of intervention participation
[c] Propensity score matching model
[d] Endogenous treatment model

We also interact intervention participation with each of the broad intervention categories (restriction on forest access and conversion, non-conditional livelihood enhancement, conditional livelihood enhancement, environmental education) to test whether different intervention types vary in their impacts on household energy. These results are presented in Appendix Table A- 2 through Table A-5. Forest access restrictions and conditional livelihood enhancements (e.g. conditional payments) do not have significantly different impacts than the other intervention types. However, non-conditional livelihood enhancements induce significantly more households to adopt ICS technology than other interventions, and these effects are amplified by the presence of REDD+. Similarly, while environmental education initiatives in control villages are less effective at promoting improved biomass stoves, this decreased effectiveness is not seen in REDD+ environmental education interventions.

3.2.4 How do deforestation and forest degradation interventions affect lower income households?

Results of DDD regression models interacting a low-income indicator with presence of REDD+ and intervention participation are presented in Table A- 6 for traditional cooking technology and Table A- 7 for cleaner technology. We do not find that REDD+ initiatives are impacting low-income households differently than middle-income and high-income households. However, participation in an intervention targeting deforestation or forest degradation does have different impacts for low-income households. In the propensity-matched sample, low-income households participating in deforestation interventions are less likely to move away from three-stone fire and fuelwood as their primary cooking technology and fuel as compared to higher income households participating in deforestation interventions. They are also more likely to switch to improved stoves and less likely to shift to LPG in the propensity score model. However, the endogenous treatment model produces significant sign changes for all four household energy outcomes. Thus, these results are highly sensitive to model specification, and in general we cannot make any robust conclusions about the distributional impacts of deforestation and forest degradation interventions.

4. Conclusion

Our analysis adds to the sparse body of literature on empirical program evaluations of REDD+, including only one other study that examines the influence of REDD+ on household energy choices (Sharma et al., 2015). We provide evidence that REDD+ interventions encourage adoption of improved cookstoves in the case of Tanzania where the REDD+ initiatives specifically promoted ICS. Our results also suggest that interventions targeting deforestation and forest degradation are effective at shifting households from fuelwood and three-stone fire use to LPG. The fact that interventions are present in both REDD+ and control villages indicates that the GCS study sites attract a large amount of international and local NGO activity. This creates challenges to understanding the additionality of REDD+ initiatives and is addressed in our DDD models. While REDD+ does not appear to increase overall effectiveness among the full sample of interventions, we find that non-conditional livelihood and environmental education interventions are most effective at incentivizing adoption of cleaner cooking technology, particularly REDD+ villages.

In conducting rigorous impact evaluations, it is critical to account for endogenous selection in not only site selection, but also household participation in interventions (Pattanayak, 2009). While there is a growing suite of methods to deal with these econometric problems, in this project we rely on the popular approaches of propensity score matching and endogenous treatment regression models to recover the true causal impact of participation in an intervention focused on reducing deforestation and forest degradation. To deal with site selection, we relied on the propensity score matching reported in Sills et al. (2017), which showed that REDD+ sites were located in villages that received previous external development support and had households with fewer assets and less access to public services. To deal with endogenous participation, the first stage of the endogenous treatment model shows that households with more land and with greater baseline reliance on forests are more likely to participate. In addition to correction for potential selection biases, these approaches provide insights about group and household level behaviors – that is, why some places are chosen and why some people participate. Ultimately, compared to models that do not account for endogenous selection, we find that treatment effects are generally greater in magnitude and in some cases are more significant.

We reiterate that the majority of households did not adopt new fuel sources or cooking technologies. Particularly in the case of Tanzania, overall use of ICS and LPG remains low, while fuelwood and three-stone fire use remains high. There is substantial inertia in the choice of cooking technology, perhaps not surprisingly given the up-front investments required to switch to ICS or LPG (Jeuland et al., 2015). It is also possible that not enough time had passed for impacts on household energy to fully surface since follow-up surveys were conducted only a few years after intervention implementation.

Recognizing that household energy is not the primary objective of REDD+, the ineffectiveness of REDD+ in promoting cleaner cooking technology is not necessarily indicative of a failure of REDD+ to meet its primary goal of reducing carbon emissions from deforestation and forest degradation. However, if non-carbon health and welfare impacts of cleaner cooking technology are of interest to REDD+ proponents as a way to meet social safeguard requirements, our findings still have important implications for the design of future REDD+ initiatives. The type of intervention seems to matter: while conditional payments do not appear to be effective, non-conditional livelihood strategies and environmental education are effective. Finally, the larger estimated effects in Tanzania suggest that if REDD+ proponents focused on promoting household energy transitions, they could shift households to cleaner fuels and more efficient cooking technologies, with benefits for both the climate and local health and well-being.

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Appendix

Table A- 1. Variable Balance

Variable	Sample	Normalized Difference	T-Test	
			T-Statistic	P-Value
Low Income	Unmatched	-11.7	-3.04	0.002
	Matched	-4.9	-1.47	0.142
Log(Total Assets)	Unmatched	59.1	15.51	0.000
	Matched	2.1	0.67	0.503
Log(Total Land)	Unmatched	102.5	25.13	0.000
	Matched	-1.7	-0.47	0.637
Insecure Tenure	Unmatched	-0.1	-0.02	0.988
	Matched	2.1	0.63	0.528
Received Previous NGO Support	Unmatched	-6.4	-1.73	0.084
	Matched	-4.6	-1.42	0.156
Received Previous Government Support	Unmatched	-11.9	-3.24	0.001
	Matched	0.3	0.12	0.902
Years of Education	Unmatched	-6.3	-1.62	0.105
	Matched	4.7	1.38	0.168
Gender	Unmatched	-10.1	-2.67	0.008
	Matched	1.2	0.38	0.704
Age	Unmatched	2.1	0.54	0.592
	Matched	0.4	0.11	0.911
Household head ethnicity	Unmatched	-17.7	-4.51	0.000
	Matched	-0.8	-0.25	0.804
Household head born in village	Unmatched	-27.1	-7.10	0.000
	Matched	-8.3	-2.51	0.012
Years household head has lived in village	Unmatched	-30.3	-7.93	0.000
	Matched	-0.2	-0.07	0.940
Dependency ratio	Unmatched	3.3	0.84	0.400
	Matched	-3.4	-1.00	0.319
Household size	Unmatched	1.6	0.40	0.687
	Matched	-0.7	-0.19	0.845
Poor housing condition	Unmatched	-21.4	-5.59	0.000
	Matched	-10.7	-3.19	0.001

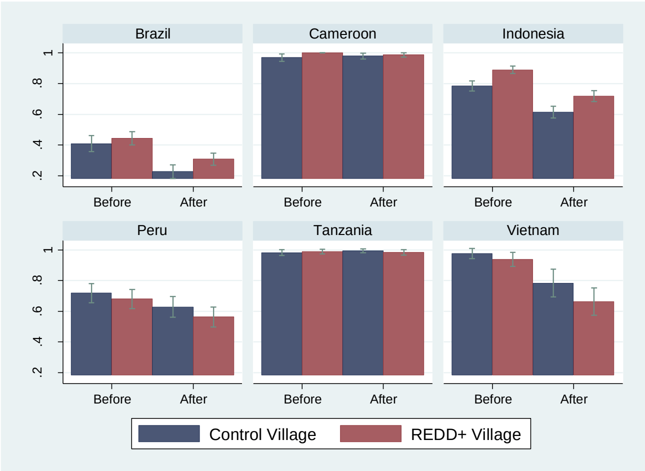

Figure A- 1. Households using fuelwood

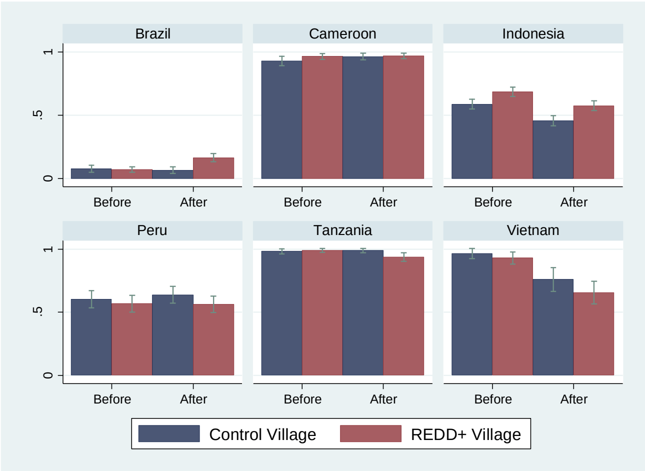

Figure A- 2. Households using a Three-Stone Fire

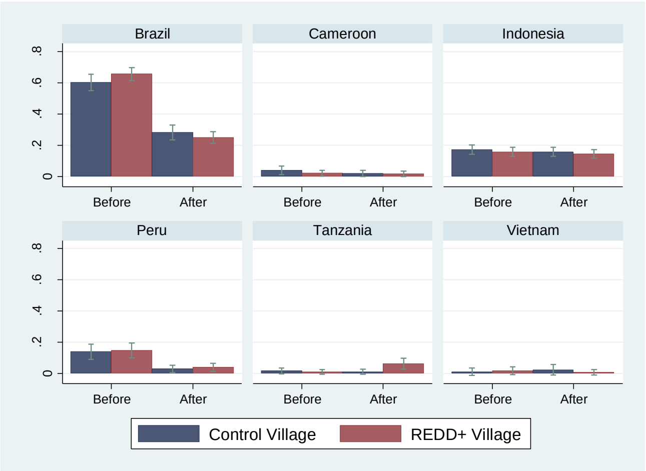

Figure A- 3. Households using an improved biomass stove

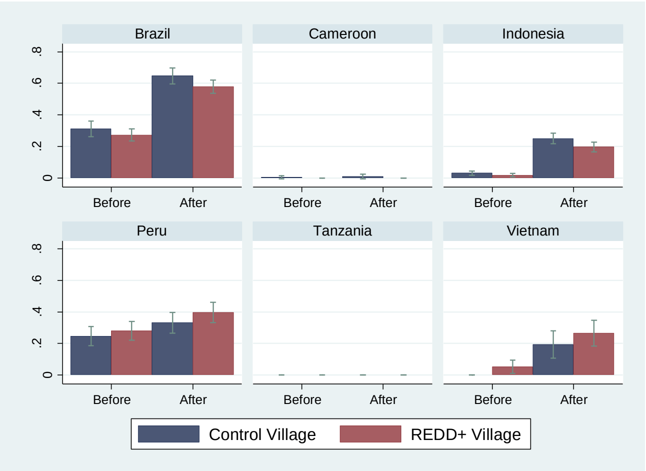

Figure A- 4. Households using LPG

Table A- 2. Intervention Type: Forest use and access restrictions (FAR)

VARIABLES	(1) Fuelwood	(2) Three-Stone Fire	(3) Improved Biomass Stove	(4) LPG
REDD+ village	0.0523 (0.0427)	0.0535 (0.0459)	-0.00507 (0.0104)	0.0403 (0.0399)
Intervention participation	0.333*** (0.0895)	0.274 (0.293)	-0.173*** (0.0305)	0.385*** (0.0578)
REDD+ village x Intervention	0.0554 (0.0423)	0.0557 (0.0515)	-0.00471 (0.0114)	0.0356 (0.0489)
Intervention x FAR	0.00808 (0.0498)	-0.000643 (0.0687)	0.00580 (0.0138)	0.00359 (0.0540)
REDD+ village x Intervention x FAR	0.0307 (0.0483)	0.0622 (0.0616)	0.0271 (0.0165)	0.0157 (0.0530)
Constant	-0.0786* (0.0450)	-0.0276 (0.151)	0.109*** (0.0214)	-0.104*** (0.0295)
Observations	1,707	1,713	1,713	1,713

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Estimated using endogenous treatment model

Table A- 3. Intervention Type: Non-conditional livelihood enhancement (NCLE)

VARIABLES	(1) Fuelwood	(2) Three-Stone Fire	(3) Improved Biomass Stove	(4) LPG
REDD+ village	0.0519 (0.0424)	0.0536 (0.0459)	-0.00492 (0.0104)	0.0403 (0.0399)
Intervention participation	0.333*** (0.0791)	0.250 (0.262)	-0.182*** (0.0303)	0.378*** (0.0505)
REDD+ village x Intervention	0.109** (0.0511)	0.110* (0.0579)	-0.00171 (0.00753)	0.0678 (0.0491)
Intervention x NCLE	0.0282 (0.0537)	0.0729 (0.0663)	0.0317** (0.0152)	0.0248 (0.0601)
REDD+ village x Intervention x NCLE	0.0294 (0.0408)	0.0772 (0.0551)	0.0254** (0.0103)	0.0218 (0.0442)
Constant	-0.0823* (0.0428)	-0.0296 (0.145)	0.109*** (0.0215)	-0.105*** (0.0297)
Observations	1,707	1,713	1,713	1,713

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Estimated using endogenous treatment model

Table A- 4. Intervention Type: Conditional livelihood enhancement (CLE)

VARIABLES	(1) Fuelwood	(2) Three-Stone Fire	(3) Improved Biomass Stove	(4) LPG
REDD+ village	0.0520	0.0538	-0.00504	0.0400
	(0.0425)	(0.0461)	(0.0104)	(0.0396)
Intervention participation	0.353***	0.268	-0.172***	0.397***
	(0.0831)	(0.309)	(0.0300)	(0.0495)
REDD+ village x Intervention	0.0671	0.0816	0.00112	0.0546
	(0.0433)	(0.0562)	(0.0107)	(0.0449)
Intervention x CLE	-0.0781	-0.0338	0.00760	-0.0481
	(0.0476)	(0.103)	(0.0206)	(0.0826)
REDD+ village x Intervention x CLE	-0.0213	0.0100	0.0141	-0.0327
	(0.0415)	(0.0676)	(0.0139)	(0.0445)
Constant	-0.0821*	-0.0220	0.109***	-0.107***
	(0.0449)	(0.172)	(0.0216)	(0.0296)
Observations	1,707	1,713	1,713	1,713

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Estimated using endogenous treatment model

Table A- 5. Intervention Type: Environmental education (EE)

VARIABLES	(1) Fuelwood	(2) Three-Stone Fire	(3) Improved Biomass Stove	(4) LPG
REDD+ village	0.0522	0.0535	-0.00500	0.0403
	(0.0426)	(0.0459)	(0.0104)	(0.0399)
Intervention participation	0.339***	0.288	-0.163***	0.393***
	(0.0865)	(0.276)	(0.0300)	(0.0524)
REDD+ village x Intervention	0.0255	0.0330	-0.0123	0.0146
	(0.0394)	(0.0563)	(0.0109)	(0.0447)
Intervention x EE	-0.00557	-0.0378	-0.0235**	-0.0233
	(0.0533)	(0.0555)	(0.0116)	(0.0602)
REDD+ village x Intervention x EE	0.0575	0.0667	0.0117	0.0253
	(0.0519)	(0.0757)	(0.0132)	(0.0493)
Constant	-0.0793*	-0.0297	0.109***	-0.104***
	(0.0462)	(0.154)	(0.0215)	(0.0299)
Observations	1,707	1,713	1,713	1,713

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Estimated using endogenous treatment model

Table A- 6. Income Distribution, Traditional Technology

	Fuelwood			3-Stone Fire		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	REDD+ [a]	Intervention, PSM [b]	Intervention, ET [c]	REDD+ [a]	Intervention, PSM [b]	Intervention, ET [c]
Low Income	0.0197	-0.0360	0.0545*	0.0208	-0.0234	0.0295
	(0.0263)	(0.0321)	(0.0323)	(0.0275)	(0.0312)	(0.0552)
REDD+ village	-0.00283			0.0122		
	(0.0376)			(0.0395)		
REDD+ village x low income	-0.0330			-0.0329		
	(0.0335)			(0.0353)		
Interv. participation		-0.0659***	0.325**		-0.0299	0.176
		(0.0235)	(0.146)		(0.0304)	(0.360)
Interv. participation x low income		-0.0782***	0.00620		-0.0616**	-0.0202
		(0.0285)	(0.0205)		(0.0307)	(0.0340)
Household head born in village	-0.0356*	-0.0229	-0.0377	-0.0424**	-0.0270	-0.0429*
	(0.0201)	(0.0203)	(0.0287)	(0.0208)	(0.0225)	(0.0255)
Poor housing condition	-0.0884***	-0.0711***	-0.0730**	-0.0792***	-0.0578**	-0.0686**
	(0.0217)	(0.0199)	(0.0328)	(0.0245)	(0.0243)	(0.0339)
Constant	0.196***	0.198***	-0.00691	0.216***	0.202***	0.105
	(0.0300)	(0.0306)	(0.0807)	(0.0315)	(0.0317)	(0.206)
Observations	2,038	1,309	1,707	2,044	1,314	1,713
R-squared	0.020	0.024		0.017	0.013	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Intent-to-treat model
[b] Propensity score matching model
[c] Endogenous treatment model

Table A- 7. Income Distribution, Cleaner Technology

	Improved Biomass Stove			LPG		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	REDD+ [a]	Intervention, PSM [b]	Intervention, ET [c]	REDD+ [a]	Intervention, PSM [b]	Intervention, ET [c]
Low Income	0.00995	0.0115	-0.0130	0.0158	-0.0262	0.0609**
	(0.0119)	(0.0135)	(0.0130)	(0.0258)	(0.0304)	(0.0281)
REDD+ village	0.0163			-0.00579		
	(0.0117)			(0.0386)		
REDD+ village x low income	0.000654			-0.0293		
	(0.00790)			(0.0350)		
Interv. participation		0.0282**	-0.162***		-0.0564**	0.392***
		(0.0131)	(0.0260)		(0.0254)	(0.0510)
Interv. participation x low income		0.0121	-0.0187*		-0.0693**	0.0103
		(0.0101)	(0.00981)		(0.0285)	(0.0209)
Household head born in village	-0.00480	-0.00510	-0.00356	-0.0318	-0.0178	-0.0350
	(0.00673)	(0.00904)	(0.00911)	(0.0194)	(0.0196)	(0.0299)
Poor housing condition	0.0159*	0.0233**	0.0105	-0.0870***	-0.0714***	-0.0751**
	(0.00845)	(0.0111)	(0.0113)	(0.0215)	(0.0186)	(0.0340)
Constant	0.0103*	0.000700	0.108***	0.184***	0.179***	-0.0527*
	(0.00564)	(0.00646)	(0.0209)	(0.0309)	(0.0288)	(0.0319)
Observations	2,044	1,314	1,713	2,044	1,314	1,713
R-squared	0.006	0.011		0.020	0.023	

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
[a] Intent-to-treat model
[b] Propensity score matching model
[c] Endogenous treatment model