FOOD WITHOUT FIRE: NUTRITION IMPACTS FROM A SOLAR STOVE FIELD EXPERIMENT

by

Laura Elizabeth McCann

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As members of the Master's Committee, we certify that we have read the thesis prepared by: Laura E. McCann
titled: Food Without Fire: Nutritional Impacts from a Solar Stove Field Experiment

and recommend that it be accepted as fulfilling the thesis requirement for the Master's Degree.

Jeffrey D. Michler
Jeffrey D. Michler — Date: Aug 17, 2021

A J Josephson
Anna Josephson — Date: Aug 17, 2021

Laura A. Bakkensen
Laura A. Bakkensen — Date: Aug 17, 2021

Final approval and acceptance of this thesis is contingent upon the candidate's submission of the final copies of the thesis to the Graduate College.

I hereby certify that I have read this thesis prepared under my direction and recommend that it be accepted as fulfilling the Master's requirement.

Jeffrey D. Michler
Jeffrey D. Michler — Date: Aug 17, 2021
Thesis Committee Chair
Department of Agricultural and Resource Economics

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One would think that by now, I would have learned how to distill a set of complexities into something tractable. Instead, I'm staring at my computer wondering how anyone is ever able to convey their gratitude for so much with so little space.

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DEDICATION

For Z, M, and H.

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ABSTRACT

Population pressure is speeding the rate of deforestation in Sub-Saharan Africa, raising the monetary and opportunity costs of meal preparation. Many people rely on firewood or charcoal to prepare food. Using a field experiment in Western Zambia, we investigate the impact of solar cook stoves on compositional changes in diet when constraints to cooking nutritionally diverse foods (e.g., legumes) and the cost of meal preparation are removed. We find no impact on diet for those households assigned to the solar stove treatment. We do see a significant result for the average number of dishes per household meal. These results offer valuable insights into program development for the provision of solar stoves to reduce the cost of meal preparation.

CHAPTER 1

Introduction

Increasing population pressure across Sub-Saharan Africa (SSA) has accelerated household over-consumption of natural resources. In rural areas, households dependent on solid fuels (e.g., wood, animal dung, agricultural waste, charcoal, and coal) as the primary source of energy for cooking their meals (Riva et al. 2017) face increased monetary and opportunity costs of procuring fuel inputs for meal preparation. As access to energy inputs for meal preparation declines, households are unable to obtain the health benefits of a nutritionally diverse diet. We investigate the impact of alleviating constraints to cooking fuel costs on changes in dietary outcomes for households in Western Zambia.

To examine the link between rising cooking fuel costs and dietary outcomes we conduct a solar stove field experiment in the Barotse region of Zambia‘s Western Province. We randomize the assignment of solar stoves to 54 households across three communities. In total, 143 households participated in the experiment and kept detailed dietary records, regardless of treatment status, for six weeks. Households recorded the ingredients used in preparing each dish for each meal on each day plus the fuel used to prepare each dish. These data provide information on household choices in preparing the 126 meals (on average, 315 separate dishes) consumed over the study period. We randomize the delivery of solar stoves across these four groups to understand which information, from which activity, and which socio-economic factors might have a larger impact on shifting people towards more diverse diets, particularly when there is access to a low-cost source of energy for cooking. We then use the exogenous variation provided through randomization of solar stove recipients to identify the impact of solar stoves on improving household dietary outcomes.

We find that households assigned solar stoves used the stove to prepare 40% of the dishes consumed throughout the experimental time period. We find no significant effect of solar stove assignment nor use on measures of household dietary diversity, total legumes cooked, nor total number of dishes in a given meal. We see a weak, significant, and positive relationship between solar stove use and the average number of lunch dishes prepared for a given household.

Our results are consistent with other experiments featuring clean cookstove adoption and health outcomes (Hanna et al. 2016; Beltramo and Levine 2013; Iessa et al. 2017), and with prior impacts of nutrition-specific interventions on dietary outcomes in Zambia (Kumar et al. 2018; Rosenberg et al. 2018). While solar stoves appear to be well-positioned as a unique solution to the growing list of social and environmental stressors associated with climate change, there remains a disjuncture between their conceptualization and implementation.

We pose a theoretical framework using the unitary agricultural household model (Singh et al. 1986) and draw upon the work of (Fitzsimons et al. 2016) to model the impacts of increased protein consumption through a household member‘s choice to integrate more legumes into their diet subject to the constraints of labor supply and available funds for purchasing non-legume goods.

We contend that when the time and cost burdens of procuring cooking fuel are reduced by the provisioning of solar stoves, households will be better equipped to allocate time and money to sourcing more diverse ingredients for meal preparation.

We then conduct an empirical analysis of the average, intent-to-treat, and local average treatment effects. We use our rich dataset of over 28,000 dish-level observations over a six-week period to estimate impacts on solar stove assignment on use, solar stove assignment on the share of meals cooked on a solar stove, household dietary diversity scores, dietary species richness scores, the average number of dishes in a given meal, the total number of meals skipped, and the total instances of cooking legumes.

Our findings join an understudied space of health outcomes associated with solar stove adoption and our results inform the literature on development practice in socio-ecological systems. Understanding the effectiveness of multi-dimensional interventions such as the one discussed in this paper is integral to building resilient, healthy communities.

CHAPTER 2

Background

2.0.1 Food Security and Nutrition

Institutional definitions of food security have evolved considerably since the early efforts of food aid for development. In recent decades, the aim to ensure food availability and accessibility has evolved towards nutritional quality in order to mitigate global malnutrition and hunger (Klennert 2009). This shift has necessarily inspired the development of new metrics for a deeper assessment of food insecurity that addresses the dimensions of availability, accessibility, utilization, and stability/vulnerability (Pangaribowo et al. 2013). Several metrics and frameworks have emerged to capture each of these dimensions, including the Poverty and Hunger Index and Global Food Security Index, anthropometric indicators, and dietary diversity scores, and others (Pangaribowo et al. 2013). We focus specifically on measures of dietary diversity, as recent research in the BFS has established the need for crop diversification strategies to both increase access to a broader range of nutrients and mitigate shocks associated with increasing climate variability.

Empirical evidence suggests that more diverse diets improve several broader health outcomes, including increased birthweight and reduced hypertension (Ruel 2003; Pangaribowo et al. 2013). Dietary diversity scores are fairly straightforward to calculate and lower the barriers to their use in analysis (Pangaribowo et al. 2013). The diets of households across the BFS comport with the observation from Ruel (2003) that many household diets in developing countries are centered around "starchy staples and often include little or no animal products and few fresh fruits and vegetables" (Pasqualino et al. 2016). We see this reflected in our own sample, as cereals were the most frequently consumed food group among participants (see Table A1), with porridge, maize, maize flour, and cassava occupying four of the top six most frequently consumed ingredients among our sample (see Table A2). Kumar et al. (2018) state that much of the dependence of rural Zambians on these crops is due to large-scale maize subsidy programs that create intense pressure to produce only maize, and that "rural Zambian diets are monotonous and generally lack the diversity required for good nutrition."

Growing interest in integrated nutrition interventions is actively changing the way nutrition outcomes are studied (Rosenberg et al. 2018). Such interventions emphasize the conceptualization of nutrient insecurity as a function of one's socio-ecological surroundings (Kumar et al. 2018). Nutrition-sensitive landscape programming aims to introduce comprehensive and practicable solutions for the needs of a socio-ecological system. Under the auspices of World Fish and Bioversity International, the Agricultural and Aquatic Systems (AAS) program operated a pilot program promoting improved nutrition and climate-smart agricultural practices in the BFS from (2014-2015) (del Río 2014; Pasqualino et al. 2015b, 2016). A team of researchers conducted a set of qualitative studies on seasonal food availability, governance systems, and market functionality to triangulate the issues of food and nutrition security in the BFS (Madzudzo et al. 2013; Pasqualino et al. 2015a,b, 2016). The findings from these studies guide our experimental design and selection of outcome variables. We use the Household Dietary Diversity Score and Dietary Species Richness indicators to analyze changes in dietary composition in response to the provisioning of solar stoves. Similar to the construction of the HDDS, the DSR scores are a count of the species included in a dish (Lachat et al. 2018). Including an additional measure provides validation and gives a clearer understanding of the nutrient and biological diversity of a household's diet and allows us to validate the household dietary diversity scores and compare the results (Lachat et al. 2018).

2.0.2 The Barotse Floodplain System

Spanning roughly 230 km, the BFS includes four districts in Zambia's Western Province and is home to over 225,000 residents (Emerton 2003; Zimba et al. 2018). The BFS is inundated annually from December to March from the flooding of the Upper Zambezi River (Pasqualino et al. 2016). This yearly event revitalizes the soil and facilitates the agricultural livelihoods of 90% of the individuals in the region (Pasqualino et al. 2016; Baars and Ottens 2001; Turpie et al. 1999; Mirriam Sampa et al. 2019; Flint 2008).

The Lozi people are the largest ethnic group in the region and maintain oversight of the area's agricultural operations through the Barotse Royal Establishment governing body (Pasqualino et al. 2016). The migratory patterns of the Lozi are adapted to the natural flow of the Zambezi River and move twice annually: to the upland during the flooding season and to the lowland when the water recedes (Baars and Ottens 2001; Pasqualino et al. 2016; Cai et al. 2017; Joffre et al. 2017; Rickert 2013). The Lozi are primarily subsistence households earning their livelihoods by crop production, fishing, and cattle grazing (Pasqualino et al. 2016).

The BFS experiences severe poverty and is vulnerable to shocks (Flint 2008; Rajaratnam et al. 2015). Its aforementioned ecological barriers are compounded by limited access to agricultural inputs (e.g., dung), equipment, and household knowledge about improved management techniques using organic matter (Baidu-Forson et al. 2014). The region experiences a period of four to five months with limited access to food known as the hunger season (Castine et al. 2013; Baidu-Forson et al. 2014; Rajaratnam et al. 2015; Pasqualino et al. 2015b). The BFS has garnered attention from researchers for its low agricultural productivity despite its abundance of natural resources (Flint 2008). Historically, floodplain environments have served an integral role in sustaining life through their natural replenishment of nutrients vital to aquatic and terrestrial systems. In recent decades, this seasonal dependence has evolved into what Cole et al. (2018) characterize as a social-ecological trap, where rapid population growth and overexploitation of natural resources have created a cycle of poverty and food insecurity. Concurrent with market failures, poor institutional oversight, and lack of information sharing, the effects of increased climate variability are becoming more evident. Impacts from climate change include protracted regrowth periods of deforested lands, unpredictable droughts and flooding (Mirriam Sampa et al. 2019). Flint (2008) demonstrates decreasing rainfall trends in BFS planting seasons from 1960-2000 and increased frequency and length of extreme heat days over time; however the author clearly highlights the possible error introduced by the region's lack of data resources. Flint (2008) tempers the potential of reduced data quality from the BFS with qualitative descriptions of BFS households and livelihoods with respect to changes in climate patterns. Participants' lived experiences corroborate the climatological trends of decreased predictability and adverse impacts on agricultural production in the floodplain.

Lozi households experience high levels of food insecurity and poverty (Pasqualino et al. 2016). In general the region lacks the infrastructure for market access and households practice subsistence agriculture (Flint 2008; Pasqualino et al. 2016). Common regional crops include maize, sweet potatoes, cassava, and rice (de Silva 2014). Regional crop availability varies, as in some villages certain crops are available year-round, while other villages can only access such crops for a three-month period (Pasqualino et al. 2015b). Community focus group sessions facilitated by Bioversity researchers in 2014 revealed that food is typically "plentiful" in Lealui and Nalitoya and "less available" in Mapungu during the months of March and April (Pasqualino et al. 2015b). In both cases, the experiment was conducted several months ahead of the hunger season, which starts as early as August and lasts until December. As part of the community focus groups, participants were asked to rate the availability of different food groups corresponding to the FAO dietary diversity guidelines. Of the legumes, beans, seeds, and nuts group, no native crops were considered to be of "high" availability at any point during the year. The Bambara groundnut was rated as "low" and "medium" availability," while cowpeas and groundnuts were rated as "low availability" during the months of March and April (Pasqualino et al. 2015b). Other nuts used for creating cooking oil, like *mungongo*, were rated with "medium" availability, but processed culinary ingredients such as these contribute less to dietary diversity and overall nutrition (Kennedy et al. 2010). Caterpillar and fish were rated with the highest availability (medium) out of all options for animal source food (Pasqualino et al. 2015b). During the annual fishing ban, households substitute legumes (beans and groundnuts) for fish to meet their nutritional needs for protein uptake, which drives the price per unit of beans and other legumes up during the fishing ban Pasqualino et al. (2015a). Although the price of legumes does increase during the fishing ban, vendors do observe decreased prices following the end of the fishing ban (Pasqualino et al. 2015a), which would have coincided with the beginning of our experiment.

Households in the region have also self-selected into nutritional cooking clubs, participation in farm plot demonstrations (learning plots), participation in both, or chosen to abstain from participation in these development activities. These programs have promoted the introduction of legumes into the Lozi diet as both an inexpensive diet enhancement providing better access to protein and a crop with restorative properties that improve soil for farming. However, given substantial household reliance on firewood or charcoal as the main sources of energy for cooking, the longer cooking times associated with preparing legumes or other, longer-cooking foods can increase the use of cooking fuels. With climbing prices of energy inputs for meal preparation, households are less able to meet their nutritional needs as they choose to prepare a small number of quick-cooking foods, such as corn meal, rather than legumes (Barbieri et al. 2017).

2.0.3 Solar Cookstoves

While solar stove technology has existed for centuries, improved solar stoves entered the development discourse in the latter half of the twentieth century (Wentzel and Pouris 2007), gaining popularity as a valuable tool for alleviating the opportunity and financial cost burdens of cooking fuel (Biermann et al. 1999). Experiments for evaluating solar cookers have become more popular following the endorsement of the United Nations through their Sustainability for All plan aimed towards improved cookstove adoption (Bensch and Peters 2015; Iessa et al. 2017). Although solar stoves can appear to be a universal solution for several interconnected socio-ecological issues, prior experiments have shown mixed results with respect to adoption and environmental benefits. In several cases, solar stove experiments have found low to moderate adoption rates (Biermann et al. 1999; Wentzel and Pouris 2007; Ruiz-Mercado et al. 2011; Hanna et al. 2016; Iessa et al. 2017); however, there are instances of adoption success. Bensch and Peters (2020) found an almost perfect adoption rate and 30% savings on firewood consumption. Similarly, an experiment in Ethiopia from 2013-2016 revealed that nearly over two-thirds of the sample were still using their stoves at the end of the experimental time period (Mekonnen et al. 2020). Iessa et al. (2017) suggest that successful studies are those which have properly scoped their intervention within a local context. A key feature of our experiment is that it is contextualized by several previous qualitative studies and interventions to help build a specific resilience to exogenous shocks. While the stoves are a prominent part of our analysis, the primary focus is on nutritional outcomes. Our reseach leverages local context while also contributing to the broader literature on health outcomes for solar stoves, which at present is generally limited to respiratory conditions (Hanna et al. 2016; Bensch and Peters 2015; Smith-Sivertsen et al. 2004; Mobarak et al. 2012; Iessa et al. 2017).

CHAPTER 3

Theoretical Framework

The goal of our intervention is to promote greater dietary diversity by reducing the fuel cost burden associated with integrating new foods into household diets. In this section, we pose a theoretical framework that explores the impact of using solar stoves on changes in legume consumption in particular. Qualitative findings from previous assessments of nutrition security and crop production in the BFS suggest that including more legumes in household diets may offer a sustainable solution to both nutrition insecurity and soil degradation (del Río 2014; Pasqualino et al. 2016). While BFS households have expressed interest in preparing legume-based meals and diversifying their diets (del Río 2014; Pasqualino et al. 2016), the additional time and money towards procuring greater amounts of fuel to sustain extended cooking times becomes cost-prohibitive. We aim to reduce the primary barriers to legume consumption by providing an alternative cooking method that alleviates the time and financial burdens of sourcing cooking fuel. Ideally, treated households will choose to use their solar stoves to prepare more legume-based meals. We use a unitary agricultural household model to capture changes in consumption following the solar stove intervention. Drawing from (Singh et al. 1986) and (Fitzsimons et al. 2016), we model BFS households as both producers and consumers.

We begin by assigning a time endowment T to the household. We define household labor l as a function of the time endowment and leisure L, such that:

$$l = T - L.$$

We assume the household's utility is a function of leisure L, consumption of non-food goods

G, and nutrition N. The household will maximize its utility as a function of food inputs and labor supply such that the total expenditure on all goods (G, X_1, and X_2) does not exceed total income, which is expressed as a product of wages w and hours of labor as a function of time and leisure $T - l$. The household's problem then is:

$$\begin{aligned} \max_{G,L,X_1,X_2} \quad & U(G, L, N), \\ \text{s.t.} \quad & G + p_1 X_1 + p_2 X_2 \leq w(T - L). \end{aligned}$$

The household, as a producer, is represented by the nutrition production function in Equation (3.1), where nutrition depends on the production of goods X_1 (legume crops) and X_2 (all other goods):

$$N = F(X_1, X_2).$$

Taken together, the household's problem is:

$$\begin{aligned} \max_{G,L,X_1,X_2} \quad & \mathrm{G}^{\alpha} L^{\beta} {X_1}^{\gamma_1} {X_2}^{\gamma_2} \\ \text{s.t.} \quad & G + p_1 X_1 + p_2 X_2 \leq w(T - L). \end{aligned}$$

Similar to Fitzsimons et al. (2016), we assume a Cobb-Douglas utility and production functions. We also assume that households will exhaust their budget. Given a binding budget constraint, We solve for G and substitute (3.1) into the objective function:

$$\max_{L,X_1,X_2} \quad (w(T - L) - p_1 X_1 - p_2 X_2)^{\alpha} L^{\beta} {X_1}^{\gamma_1} {X_2}^{\gamma_2}, \tag{3.1}$$

where positive parameters α, β, γ_1, and γ_2 are output elasticities for G, L, X_1, and X_2. γ_1, and γ_2 represent the household's perceived returns to nutrition inputs (legumes and nonlegumes, respectively). Household perceptions of the returns to their nutrition inputs will inform their allocation of money to non-food goods and time to labor.

We use comparative statics to ascertain whether the intervention influences how households assigned solar stoves value the nutritional benefits from cooking legumes. We take the first-order conditions:

$$N_{X_1}(L, X_1, X_2) \equiv \frac{-\alpha p_1}{w(T-L) - p_1 X_1 p_2 X_2} + \frac{\gamma_1}{X_1} = 0, \tag{3.2a}$$

$$N_{X_2}(L, X_1, X_2) \equiv \frac{-\alpha p_2}{w(T-L) - p_1 X_1 p_2 X_2} + \frac{\gamma_2}{X_2} = 0, \tag{3.2b}$$

$$N_L(L, X_1, X_2) \equiv \frac{-w\alpha}{w(T-L) - p_1 X_1 p_2 X_2} + \frac{\beta}{L} = 0. \tag{3.2c}$$

We apply Cramer's Rule using the equation system below to find solutions for our variables of interest.

$$\frac{dX_1}{d\gamma_1} = \frac{-F_{x_1\gamma_1}(F_{X_2X_2}F_{LL} - F^2{}_{X_2L})}{|\bar{H}|}, \tag{3.3a}$$

$$\frac{dX_2}{d\gamma_1} = \frac{-F_{X_1\gamma_1}(F_{X_1X_2}F_{LL} - F_{X_1L}F_{X_2L})}{|\bar{H}|}, \tag{3.3b}$$

$$\frac{dX_2}{d\gamma_1} = \frac{-F_{X_1\gamma_1}(F_{X_1X_2}F_{X_2L} - F_{X_1L}F_{X_2X_2})}{|\bar{H}|}, \tag{3.3c}$$

where $\bar{H}$ is the bordered Hessian, or determinant of the coefficient matrix. Further simplifying, we arrive at the following:

$$\frac{dX_1}{d\gamma_1} = \frac{-F_{x_1\gamma_1}(F_{X_1L}(\frac{\beta p_2{}^2}{L^2 w p_1} + \frac{\gamma_2 w}{X_2^2 p_1}) - (\frac{\beta\gamma_2}{X_2{}^2 L^2})}{|\bar{H}|} > 0, \tag{3.4a}$$

$$\frac{dX_2}{d\gamma_1} = \frac{-F_{X_1\gamma_1}F_{X_1L}(\frac{\beta p_2}{wL^2})}{|\bar{H}|} < 0, \tag{3.4b}$$

$$\frac{dL}{d\gamma_1} = \frac{-F_{X_1\gamma_1}F_{X_1L}(\frac{\gamma_2}{{X_2}^2})}{|\bar{H}|} < 0. \tag{3.4c}$$

Equations (3.4a), (3.4b), and (3.4c) demonstrate the impact of solar stove interventions on the household perceptions that influence the consumption of legumes, γ_1. The equations indicate a positive change in the consumption of protein-rich foods, a negative change in non-protein rich foods, and a negative change in leisure supply, respectively. As Fitzsimons et al. (2016) note, the negative relationship with leisure supply implies a positive relationship with labor supply, which, in the absence of credit access, indicates that the household finances consumption at a higher level by increasing labor. Thus, following our intervention, households will prepare more legume-based dishes and fewer non-legume foods.

CHAPTER 4

Experimental Design

4.1 Research Questions and Objectives

We expect that deforestation across the Barotse floodplain has increased the cost of traditional cooking fuel (firewood and charcoal) to the point where the price of cooking fuel is a binding constraint on the household's decision regarding meal preparation. Households assigned a solar stove will reduce their use of traditional cooking fuel and thus reduce the costs of meal preparation. Following this reduction in fuel costs, households will prepare more healthy meals that include more ingredients and exhibit greater dietary diversity. Additionally, households will boil more liquids and cook more legumes. Conditional on reduced fuel costs, households will change the composition of dishes cooked using traditional fuel as they re-optimize their consumption decisions. These effects will likely differ for households that had previously self-selected into participating in nutrition and/or farming demonstrations compared to households that self-selected out of these activities. We investigate the following research question: Does the provisioning of solar stoves change the composition of the diet (measured by household dietary diversity, dietary species richness, count of the number of dishes, and count of the number of meals skipped) eaten by the household?

4.2 Intervention

The intervention took place in March and April 2016, which was immediately after the end of the rainy season and at the beginning of the harvest season (Pasqualino et al. 2015b). Solar stoves were randomly assigned to 54 households and 89 additional households across three communities served as control groups. Over the course of six weeks, our sample of

143 households recorded all of the ingredients used in each dish for each breakfast, lunch, and dinner meal. Participants recorded a total of 27,804 observations using food diaries (pictured in Appendix B for all meals over a six-week period. Households committed to properly manage the solar stove, record its daily usage for six weeks in the assigned form, and record fuel consumption during the same period. Participating households were entered into a raffle of the solar stoves at the end of the six week experiment, conditional on their satisfactory completion of their cooking and fuel log. This was to incentivize members of the control group, who do not receive a stove during the initial allocation of stoves, to record their data through the six weeks.

4.3 Sampling

Ten villages across the BFS are grouped into *AAS Communities* specific to the AAS program (Pasqualino et al. 2016). Seasonal crop production and accessibility to markets, education, and health care, varies across the villages (Pasqualino et al. 2015b, 2016). To eliminate any bias associated with living in a particular village, we randomly selected three villages from the ten AAS villages in which to carry out our study: Lealui, Manpungu, and Nalitoya.

To account for participants' previous exposure to related development programs, we stratified our sample by household involvement in prior programming. This strategy resulted in four sub-samples, including i) households that participated in farmer learning plots; ii) households that participated in nutrition clubs; iii) households that participated in *both* learning plots and nutrition clubs; and iv) households that participated in neither learning plots nor nutrition clubs.

In each community we facilitated an introductory day-long event. During the morning we 1) began an open discussion with participants about the objectives, commitment, and expected results from the solar cookers project; and 2) conducted a test and used some of the solar stoves to make a communal lunch, highlighting safety management and precaution measures with a hands-on experience. During the afternoon session, we invited interested participants to volunteer for the chance to have and use the solar stove during six weeks. Given that some households in each of the villages were exposed to nutrition and crop interventions delivered prior to our experiment, participants' names were divided into one bowl corresponding to an AAS Activity sub-group per village. We then drew names, without replacement, for the assignment of the solar stoves.

4.4 Data

Our analysis uses both primary and secondary data sources. We visited all treatment and control households to collect gender, age, and education data at the individual level. We also captured household-level data on household size and number of household members.

Our descriptive statistics (see Table 1) show that, on average, participants are in their late 40s (ages range from 21-80 years of age) with lower levels of assets and education. Our sample includes more females relative to males, and on average, households have seven household members. We can also see that on average, households prepare fewer breakfast dishes and skip more breakfast meals.

Each household within the treatment and control groups for each village sub-group were instructed to record the ingredients for each dish they cooked, the method used for cooking, and the price of fuel for each dish prepared, per meal, per day over a six-week period. Households were also asked to record whether liquids were boiled, the volume of liquids boiled, whether legumes were prepared, and the amount of legumes prepared for each day over the total period. A weekly total of the time or money they allocated to sourcing their cooking fuel was also recorded. A blank food diary can be found in Appendix B. To encourage members of the control groups to maintain their daily food logs, we required the treated individuals to return their stoves at the end of the trial. We then held a separate random drawing using treated and control groups to determine the permanent owners of the stoves, regardless of their treatment assignment during the trial.

We measure impacts on dietary composition using the Household Dietary Diversity Score (HDDS) metric created by the Food and Agriculture Organization (FAO). The FAO Guidelines state that the household member who oversees meal preparation record all items consumed by anyone within the household during a specified recall period (Kennedy et al. 2010). The FAO advises a 24-hour recall period, as it reduces the risk of measurement error, simplifies the data collection process, and provides a snapshot of population-level dietary trends (Kennedy et al. 2010). Ranging from 1-12, the HDDS measures a household's relative accessibility to "dietary energy" where 1 indicates low dietary diversity and 12 indicates high dietary diversity (Kennedy et al. 2010). To generate scores for each household, we matched each ingredient observation to one of the twelve FAO-designated food group categories and the appropriate level (four available) of processing. Based on pre-determined FAO standards associated with food group and processing levels, nutritious ingredients were assigned a value of one. Ingredients that offered little to no nutritional value were not counted towards the HDDS. Additionally, if a meal comprised of multiple dishes using some of the same ingredients, the repeated ingredient was only counted once for that meal. The ingredient-level scores were aggregated to the dish, meal, day, week, and six-week levels. We also calculate the HDDS as an average over the food groups within each level of aggregation.

Following Lachat et al. (2018), we include dietary species richness as an additional measure of dietary diversity. This metric is calculated by matching ingredients to species and tabulating the number of unique species consumed during a 24-hour period. Lachat et al. (2018) highlight that dietary species richness serves as an important validation tool and enriches the understanding of nutrient availability and biodiversity for a given population.

We analyze whether households are cooking more dishes, on average, after assignment to a solar stove. Since participants log the cooking methods associated with each dish, a change in average dishes per meal could tell us more about household choices to completely substitute solar stove use for fuel-based cooking methods or supplement their traditional cooking methods with solar stove use. We calculate the average number of dishes in a meal by tabulating the number of dishes for breakfast, lunch, dinner meals and dividing by the total number of meals consumed by a household over the six-week experimental period.

We consider the number of meals skipped by each household by tabulating the total number of meals skipped over the experimental period.

Based on prior qualitative research undertaken by BI, we include the number of times legumes are prepared by a household during the experimental time frame. Legumes are promoted as a less expensive substitute for animal-sourced protein, especially during the annual fishing bans. They also contribute to improved soil quality, as nitrogen-fixing bacteria facilitate the breakdown of atmospheric nitrogen and release it into the soil.

We also used Landsat 8 data (see Appendix C) in order to calculate the percentage of cloud cover during the period. It is important to note that these data are incomplete, as the satellite only flew over our RCT region five times during the experiment. Thus, we use the single value obtained from Landsat 8 for each day within the week. When no data were available for a certain week, we assigned it the averaged values from the week before and week following.

We used the coefficients associated with tropical livestock units (TLU) to convert our recorded values of participants' livestock to internationally comparable units. The sum of these units is the Tropical Livestock Index (TLI) value (FAO 2018).

We also construct indicator variables for our household covariates, cooking method, fuel type, and each level of data (i.e., dish, meal, day, week, total RCT time). We validate data, including checks for obvious misspellings, case-sensitivity, and errant characters from data entry; joining dictionary files with Lozi-English translations for food groups, processing, and species; as well as interpolating missing English data by matching Lozi entries to their English counterparts. Continuous outlying values were winsorized at the 2nd and 98th percentiles.

CHAPTER 5

Empirical Approach

Our causal interpretation draws from the Potential Outcomes Framework (Rubin 2005). Within this framework, an outcome is a random variable whose realized value is contingent on exposure to a single, well-defined causal state (Morgan and Winship 2015). In the experimental case with binary treatment outcomes, participants are exposed to the causal state associated with one of two treatment statuses (treated or untreated). We then face the fundamental problem of causal inference: while the unrealized–and unobserved–outcome, known as the counterfactual, is the ideal comparative reference for assessing the effect of the intervention, it is impossible to compare an individual's observed outcome with their unobserved outcome (Holland 1986; Morgan and Winship 2015). We approximate this alternative outcome by only assigning the treatment to part of the population. However, in almost any experiment, there are sysetmatic differences among participants that may influence selection into the treatment. Thus, to ensure that no observable or unobservable factors are deterministic of the treatment assignment and a household's realized outcome, we randomly select the treated households from the pool of all participants. We then use the experimental observations to calculate an aggregate causal effect.

We desire to isolate the effect of solar stove use on nutrition outcomes. In an ideal experiment, we would calculate the Average Treatment Effect (ATE), which Angrist and Pischke (2008, 2015) describe as the difference between the treated and control groups in the absence of selection bias. As previously discussed, our randomized treatment assignment allows us to invoke the ignorability assumption and assume that random assignment has eliminated any systematic variation in the treatment due to selection bias and we may "ignore" any remaining idiosyncractic variation in the treatment (Morgan and Winship 2015). In the context of our experiment, the ATE would measure the linear difference in mean solar stove use across both groups: those who were assigned a solar stove, and those who were not. In the event of perfect compliance, we would estimate the ATE of solar stove use on household dietary diversity, for example, with the following model:

$$HDDS_{iht} = \alpha + \beta T_h + X_h' \gamma + \mu_v + \phi_g + \epsilon_{iht}, \tag{5.1}$$

where our outcome variable $HDDS_{iht}$ represents the dietary diversity score of a household h during time t; α is an intercept term; T is the household use of a solar stove to prepare a dish; and X is a matrix of controls indexed by household with γ as its coefficient. μ is a village fixed effect indexed by village v; ϕ is a fixed effect indexed by group, based on previous exposure to AAS activities; and ϵ, the idiosyncratic error term for each household h during time t.

With this understanding, and by allowing for the Stable Unit Treatment Value Assumption (SUTVA), which Morgan and Winship (2015) define as the assumption that a treated individuals outcome is not dependent on the way the treatment is assigned, we can estimate causal effects. However, our collected data include both a household's treatment status and whether a solar stove was used. We know from an inspection of our data that there was not perfect compliance, as the values for treatment assignment and use are not identical for each household. This is not uncommon among RCTs where participating individuals may opt out of their assigned treatment with no repercussions. There is an established set of participant behaviors that partition our sample into four subgroups: *always-takers*, individuals who will somehow always receive the treatment regardless of their treatment assignment; *never-takers*, individuals who will never receive the treatment, regardless of their treatment status; *defiers*, individuals who will do the opposite of their assignment status, regardless of the assignment; and *compliers*, individuals who accept the treatment which they are assigned (Angrist et al. 1996). We consider these subgroups in our estimation framework below.

5.1 Average Treatment Effects

We address two preliminary questions before analyzing our final nutrition outcomes:

1. Are treated households using their solar stoves?
   - H_0: $\mu = 0$; there is no significant difference in the number of dishes prepared using a solar stove between those who are (treated) and are not (control) assigned a solar stove.
   - H_1: $\mu > 0$; there is a positive and significant difference in dishes prepared using a solar stove between the treated and control groups.
2. What percentage of household dishes is prepared using solar stoves?
   - H_0: $\mu = 0$; there is no significant difference in the share of dishes prepared using a solar stove between those who are (treated) and are not (control) assigned a solar stove.
   - H_1: $\mu > 0$; there is a positive and significant difference in the share of dishes prepared using a solar stove between the treated and control groups.

We hypothesize that if assigned a solar stove, a household will use the stove for dish preparation. We estimate the average treatment effect for each of our two intermediate outcomes using the following equations:

- Are treated households using their solar stoves? We regress dishes prepared using a solar stove onto treatment assignment in the equation below.

$$D_{ht} = \alpha + \beta T_h + X_h' \gamma + \mu_v + \phi_g + \epsilon_{ht}, \tag{5.2}$$

  where our outcome variable D_{ht} represents the dish for each household h during time t; α is an intercept term; T is the household use of a solar stove to prepare a dish; X is a matrix of covariates indexed by household; μ is a village fixed effect indexed by village v; ϕ is a group fixed effect based on previous exposure to AAS activities; and ϵ is the idiosynchratic error term for each household h during time t. Since our dependent variable is a binary variable, we estimate this equation using a linear probability model (LPM) and a Probit model and compare the coefficients and standard errors of the former to the average marginal effects and standard errors of the latter.

- What percentage of household dishes is prepared using solar stoves? We regress the share of dishes prepared using a solar stove onto the treatment assignment and covariates.

$$S_{ht} = \alpha + \beta T_h + X_h'\gamma + \mu_v + \phi_g + \epsilon_{ht} \tag{5.3}$$

,

where our outcome variable S_{ht} represents the dietary diversity score h during time t.

5.2 Intent-to-Treat Effects

We also estimate the ITT effect, which captures the causal effect of being assigned a solar stove on our final outcomes of interest. While the ITT does not account for non-compliance, it does provide us with an understanding of the causal relationship between a household's ability to use a solar stove and various nutrition outcomes. Table A4 lists the decision rule associated with the alternative hypothesis for each of the final outcomes. We expect the provisioning of solar stoves to yield positive and significant ITT effects for HDDS, SR, and number of dishes prepared using solar stoves. We also expect a negative and significant ITT effect on the number of meals skipped.

We estimate the ITT effect for the following outcomes: HDDS (measured as a count and measured as an average), Dietary Species Richness scores (measured as a count), the average number of dishes prepared using a solar stove, and the average number of meals skipped (measured as a count and average).

1. Household Dietary Diversity Scores (HDDS): We estimate the ITT effect on the HDDS (measured as a count and average) using Poisson and Ordinary Least Squares regression, respectively. The HDDS outcome variable $HDDS_{ht}$ represents the dietary diversity score h during time t and T is the household use of a solar stove to prepare a dish:
$$HDDS_{ht} = \alpha + \beta T_h + X_h' \gamma + \mu_v + \phi_g + \epsilon_{iht}. \tag{5.4}$$

2. Dietary Species Richness (SR): We also estimate the ITT effect on the DSR measured as a count using Poisson regression. The dietary SR outcome variable DSR_{ht} represents the dietary diversity score h during time t and T is the household use of a solar stove to prepare a dish:
$$SR_{ht} = \alpha + \beta T_h + X_h' \gamma + \mu_v + \phi_g + \epsilon_{iht}. \tag{5.5}$$

Each of the ITT models above are estimated for each level of aggregation (dish, meal, day, week, and total). They are also estimated both with and without controls.

3. Average Number of Meals in a Dish Prepared Using a Solar Stove: We estimate the ITT effect on the average number of breakfast, lunch, and dinner meals prepared per meal on a solar stove using OLS regression. The outcome variable ND_{ht} represents the number of dishes h during time t and T is the household use of a solar stove to prepare a dish:
$$ND_{ht} = \alpha + \beta T_h + X_h' \gamma + \mu_v + \phi_g + \epsilon_{ht}. \tag{5.6}$$

4. Number of Meals Skipped We estimate the ITT effect on the number of total, breakfast, lunch, and dinner meals skipped (measured as a count) using Poisson regression. The outcome variable MS_{ht} represents the average number of meals skipped for each meal

type h during time t and T is the household use of a solar stove to prepare a dish:

$$MS_{ht} = \alpha + \beta T_h + X_h'\gamma + \mu_v + \phi_g + \epsilon_{ht}. \tag{5.7}$$

Each of the ITT models above are estimated for each meal type (breakfast, lunch, dinner) and overall meals. They are also estimated both with and without controls.

5.3 Local Average Treatment Effects

The LATE uses the exogenous variation of the solar stove assignment variable to instrument for endogenous solar stove use. Despite our control over the treatment assignment, we cannot control whether the stoves were used. Nor could we be certain that non-treated individuals were not able to access a stove. There are many reasons that might influence a household's decision to use an assigned stove, and these systematic decisions can increase the standard error for the estimated treatment effect coefficient and underestimate the treatment effect for individuals who comply with their assigned treatment. If we wish to better understand the effect of solar stoves on nutritional outcomes for individuals who complied with their treatment status, we can leverage the Local Average Treatment Effect (LATE). While the LATE cannot account for those whose participation is not affected by the randomization of treatment assignment (*always-takers* and *never-takers*), it can use the exogeneous assignment of the treatment as an instrument for solar stove use to give us the treatment effect for *compliers*.

We use instrumental variables (IV) estimation to recover the LATE. Following the guidance of Imbens and Angrist (1994); Angrist et al. (1996); Angrist and Pischke (2008), we first ensure that we satisfy the following assumptions:

1. The Stable Unit Treatment Value Assumption, as previously defined.

2. Non-zero average effect of the instrument on the treatment, otherwise known as a valid

first stage. The instrument is correlated with the endogenous variable.

3. Exclusion restriction: the instrument is not correlated with the error term and does not influence other determinants of the outcome variables.

4. Unconfundedness: The instrument also only affects the outcome variable through the treatment assignment.

5. Monotonicity: Recall the typology of compliance discussed above. Given that the behavior of *always*- and *never*-takers is not a response to treatment assignment, the IV estimation of the LATE cannot provide insight into their associated treatment effects. Further, the assumption of monotonicity implies that the estimated effect cannot reflect both defiers and compliers, as the treatment effect must affect everyone in the same way (Angrist and Pishke, 2008; Morgan and Winship, 2015). By monotonicity, we are able to make the assumption that there are no defiers in our sample and our LATE is the average treatment effect for the compliers.

To test assumption 1, we regress the endogenous variable on the instrument, solar stove assignment. We find that the result is significant, meaning there is a relationship between the two variables. However, the exclusion restriction is not testable and instead relies upon the argument that the random assignment of a solar stove will only impact nutritional outcomes through the endogenous solar stove use variable and thus has no direct effect on any outcomes. We demonstrate a more generalized IV regression using 2SLS below.

Our first stage regression is as follows:

$$Use_{ht} = \alpha + \delta T_h + X_h' \gamma + \mu_v + \nu_{iht} \tag{5.8}$$

In equation (5.8), we regress the endogenous treatment of solar stove use *Use* on an intercept; our exogenous instrument of random treatment assignment T, Z; a matrix of covariates, village fixed effects; and stochastic error term.

We then substitute the estimated value $\hat{Use}_{ht}$ obtained using our instrument T_h for the original endogenous Use_{ht} and estimate:

$$D_{ht} = \alpha + \beta \hat{T}_h + X_h' \gamma + \mu_v + \epsilon_{ht}. \tag{5.9}$$

5.4 Inference

We cluster our standard errors at the unit of randomization: the household. Additionally, we correct for two critical concerns within our data that may affect our standard errors: heteroskedasticity and serial correlation. For household observations across time periods, we implement Liang-Zeger cluster-robust standard errors to account for correlation within the households and across time. We implement Eicker-Huber-White robust standard errors to account for heteroskedasticity when our unit of analysis is an overall measure for the household (e.g., the six-week average of HDDS scores), as we lose the threat of correlated error terms across multiple time periods.

CHAPTER 6

Results

6.1 Average Treatment Effect

Before considering specific outcomes of interest, it is important to gain a fundamental understanding of how the treated respond to their treatment status. We do this by estimating the average treatment effects for two intermediate outcomes (presented in Tables 4 and 5). The estimated coefficients and marginal effects in Table 4 illustrate that, on average, participants assigned a solar stove used the stove to cook 40% of their dishes over the six-week experimental period. The results in Table 5 suggest that, on average, participants assigned a solar stove used the stove to prepare approximately 45% of the share of dishes at the meal, day, week, and six-week level.

6.2 Intent to Treat Effect

The ITT provides insight into a household's response to having access to a solar stove, and by extension, the ability to prepare a wider variety of dishes. The solar stove should defray the higher fuel costs that accompany dishes with greater dietary diversity, while also slowing the rate at which households consume wood for fuel.

Our estimated ITT effects illustrate the effects of being *assigned* a solar stove on changes in a household's composition of diet. The results shown in Table 6 and Table 7 tell us that households assigned a solar stove did not experience any significant changes in the food groups or levels of processing during the experimental period. Lachat et al. (2018) recommend combining the use of household dietary diversity scores and dietary species richness for a deeper understanding of food and nutrition security, as changes in dietary species richness can serve as an indicator for changes in one‘s natural environment. The estimated effects in 8 show us that there were also no significant changes in the biodiversity within the sample region during the experiment. Given that our experiment was conducted during the harvest season, it is possible that households had already made and acted upon their decisions regarding agricultural production prior to participating in the RCT. Such decisions have a direct impact on the availability of foods for rural subsistence households and local markets. Thus, there may be a lagged response to biodiversity depending on an intervention‘s synchronization with the growing season.

We consider more general outcomes focused on food security in Tables 9 and 10. In theory, access to a less expensive cooking method could allow households to spend more time and money on food, rather than the fuel required for cooking food. We do not see any treatment effects that suggest the treatment assignment impacted the quantity of meals a household cooked throughout the experiment. for households assigned a solar stove on the average number of breakfast, lunch, dinner, and overall meals.

Finally, we consider the case of increased household legume consumption, as was promoted by BI after a series of qualitative studies in AAS communities. Table 11 shows no significant effect of treatment assignment on the number of times legumes were cooked by a household at the day, week, and six-week levels. As in our discussion of increased dietary diversity and species richness, such changes may be lagged due to household decisions made prior to the experiment.

6.3 Local Average Treatment Effect

Estimating the Local Average Treatment Effect allows us to hone in on the portion of our sample that was assigned a solar stove and chose to use the solar stove. We consider the same outcome variables that were used for the ITT above. Tables 13 and 12 show us that when treated households chose to use the solar stoves they were assigned, they did not experience a change in dietary diversity. Similarly, there is no evidence of a shift in species richness for these household (see Table 14).

Column 6 in Table 15 indicates that households assigned solar stoves prepared, on average, more lunch dishes in a meal. This is a plausible result, as lunchtime is likely the part of the day with the most direct sunlight; however, when covariates are removed from the model, the effect is no longer significant. As for our measure of legume consumption (see Table 17, we see no evidence of impacts from solar stove use.

6.4 Inference

Statistical power is a crucial factor in results interpretation, as smaller samples may provide unreliable results (Michler and Josephson 2021). While our sample comprises 143 households, our unique set of collected data spans 27,804 dish-level observations. Further, we use the estimation of Local Average Treatment Effects to increase our statistical power. Figure D1 shows a power calculation for the intent-to-treat effect of household dietary diversity scores calculated as an average at the meal level (N=14,541). The power calculation indicates that the minimum detectable treatment effect is around a magnitude of 0.025. Our estimated intent-to-treat effect is -0.081, meaning that we have surpassed the minimum detectable treatment effect in magnitude and our result for this specific outcome at this level of aggregation have statistical power. Figure D2 tells a different story; despite having 27,804 observations and applying the LATE, our estimated effect for dietary species richness measured as a count at the dish level is underpowered. Taken together, we know that some of our estimated treatment effects may indeed be underpowered and prevent us from ruling out the possibility of false null results.

Future analyses should use corrections for both false discovery rate (FDR) and family-wise error rate (FWER). The former corrects for the expected proportion of rejections that are Type I errors, while the latter concerns any instance of Type I errors (Michler and

Josephson 2021).

Hypotheses regarding measures of dietary diversity and legumes cooked may be grouped together, as changes in one should imply directionally similar chanages in the other. The average number of dishes in a meal cooked and the number of meals skipped should not be grouped together. While similar, these are more general measures and do not address nutrition insecurity directly. Increased dietary diversity does not necessarily imply that more dishes will be prepared per meal; perhaps the number and type of ingredients changes, but the number of dishes in a meal prepared remains the same. The number of meals skipped is not necessarily dependent on the diversity of one's diet, and further, may be independent of the number of dishes prepared. Thus, we can correct for the family-wise error rate among hypotheses concerning dietary diversity measures (HDDS and SR). We should use Anderson sharpened q-values for FDR correction and Romano-Wolf p-values for FWER correction.

6.5 Experimental Validity

With regard to internal validity, there is a trove of analytical techniques and robustness checks to ensure empirical integrity. A natural starting point is measuring attrition, which would inform us of whether any households stopped participating in the experiment. Knowing this helps us better understand the control and treated groups during the experimental time frame and any bias incurred. While an informal review of the data suggests that attrition is likely not an issue, we can formalize this assumption by performing a Lee Bounds estimation (Lee 2009). In a similar vein, missing data are also a critical part of analysis and should be accounted for. Since participants were asked to record instances of skipping meals, we are able to distinguish and compare observations of skipped meals to blank entries.

In the event that any of our other experimental outcome variables the reveal significant treatment effects, we should also investigate potential spillover effects by regressing our outcome variables on indicators of other cooking methods (e.g., wood, charcoal, dung).

The question of external validity is less straightforward. While it can be helpful to design easily comparable development interventions in order to assess their usefulness or predict success elsewhere, there is much to be said for designing experiments that incorporate the particularities of a specific geography. It is clear that an experiment in one part of the world may be an excellent or poor fit for another. Thus, we continue to face the tradeoff between generalizable and nuanced experimental design.

Given that there was 40% compliance with the treatment status, we estimated the ITT and LATE effects for the final outcomes of dietary diversity, total number of meals skipped, average number of dishes in a meal, and total instances of legumes cooked per household. While we did not find a significant effect of solar stove use on nutrition outcomes using either the ITT or LATE, we see a weak significant result for solar stove use and the household average number of dishes in lunch meal. We are encouraged by the promise of our average treatment effect results as we continue to analyze other experimental outcomes (e.g., fuel cost savings and boiled liquids).

There are several reasons why households may not adopt solar stove use. Biermann et al. (1999); Bensch and Peters (2015); Hanna et al. (2016) credit steep learning curves associated with changes to lifelong cooking behaviors as inhibitors to adoption, and further suggest that solar stoves may be better served as a supplemental cooking method in parallel with stoves reliant on biomass fuel products. Referencing the weak associations found in their own assessment of a nutrition-sensitive intervention in Zambia on dietary outcomes, (Rosenberg et al. 2018) suggest that such interventions may not be enough to make a substantial impact on dietary outcomes in isolation. A potential point of future investigation might be the success of indirect vs. direct gains in accessibility (i.e., the impact of receiving a tool that facilitates nutrient uptake versus direct access to nutrients themselves).

The low adoption rates from a five-year randomized controlled trial in Orissa, India were linked to poor stove maintenance and no significant savings in fuel costs (Hanna et al. 2016).

Iessa et al. (2017) highlight that, among the studies included in their review of solar stove experiments, one-third of the experiments reported adoption failures due to the expenses associated with owning and operating a stove. Within the past decade, development scholars have approached such an issue by heavily subsidizing the initial purchase and maintenance of solar stoves (Hanna et al. 2016) and introducing cookers to treated households at no cost to the participants (Bensch and Peters 2015). Such factors are difficult to address with a single experiment, but may offer insight into our results.

CHAPTER 7

Conclusion

While solar stoves appear to provide a unique solution to the growing list of social and environmental stressors associated with climate change, there remains a disjuncture between their conceptualization and implementation. This paper examines nutrition outcomes associated with solar stove use in a randomized controlled trial. Our estimation of average treatment effects show that, as expected, households assigned solar stoves used them to cook roughly 40% more of their meals instead of other cooking methods, relative to the control group. We do not find a significant effect of solar stove assignment nor use on measures of household dietary diversity. We also do not see a significant effect of the provisioning of solar stoves on changes in legume consumption. We detect a weak, significant, and positive relationship for solar stove use and the average number of lunch dishes prepared for a given household.

In any intervention, researchers working among vulnerable populations must bear in mind that these individuals face significant uncertainty. While an intervention may posit an innovative and multi-faceted solution, the idea of deviating from a household's regular operations may introduce further uncertainty and influence a household's choice to adopt. Moreover, we all can understand that behavioral changes do not always happen as quickly as we would like, or at least as quickly as project resource constraints might allow. A follow-up interview with households who received the raffled solar stoves upon the original RCT completion may reveal delayed effects on nutritional outcomes. Qualitative endline surveys, when feasible, can provide insight into a project's limitations or potential improvements for any similar projects offered in the future.

Table 1: Descriptive Statistics

Variables	Obs.	Mean	St Dev.	Min	Max
Solar Stove Assignment (=1 if assigned)	143	0.378	0.486	0	1
Solar Stove Use (=1 if used)	143	0.231	0.423	0	1
AAS Group (none, nutrition clubs, learning plots, both)	143	1.825	1.140	0	3
Age (years)	143	47.59	12.44	21	80
Cloud Cover (percentage)	143	99.3	8.362	0	100
Education Attainment (none, primary, secondary, higher)	143	1.545	0.614	0	3
Gender (=1 if female)	143	0.692	0.463	0	1
Household Size (number of household members)	143	7.007	2.736	1	16
Tropical Livestock Index	143	8.093	14.36	0	95.36
Village (Lealui, Mapungu, or Nalitoya)	143	1.056	0.878	0	2

Note: Summary statistics for independent variables included in analysis (N = 143 households). The first two rows present the two main independent variables used for estimating treatment effects. The remaining rows present covariate summaries. Frequency tables for categorical covariates are also presented in Table 2.

Table 2: Categorical Covariate Frequency Table

Covariate	Category	Count	Percent	Cumulative Percent
AAS Activity Group	None	33	23.08	23.08
	Learning Plot	8	5.594	28.67
	Nutrition Club	53	37.06	65.73
	Both	49	34.27	100
Educational Attainment	None	3	2.098	2.098
	Primary	65	45.46	47.55
	Secondary	69	48.25	95.8
	Higher	6	4.196	100
Gender	Female	99	69.23	100
	Male	44	30.77	30.77
Village	Lealui	51	35.66	35.66
	Mapungu	33	23.08	58.74
	Nalitoya	59	41.26	100

Note: Frequency of each categorical covariate within the sample ($N = 143$ households).

Table 3: Descriptive Statistics: Outcome Variables

Variables	Obs.	Mean	St Dev.	Min	Max
Solar Stove Assignment	27,804	0.395	0.489	0	1
Solar Stove Use	27,804	0.181	0.385	0	1
Avg. Share of Dishes Prepared Using Solar Stoves: Meal	14,541	0.178	0.357	0	1
Avg. Share of Dishes Prepared Using Solar Stoves: Day	5,526	0.178	0.298	0	1
Avg. Share of Dishes Prepared Using Solar Stoves: Week	838	0.181	0.273	0	1
Avg. Share of Dishes Prepared Using Solar Stoves: Total	143	0.177	0.258	0	0.933
HDDS Count: Dish	27,804	2.32	0.999	1	6
HDDS Count: Meal	14,541	3.897	1.53	1	9
HDDS Count: Day	5,526	5.699	1.477	1	11
HDDS Count: Week	838	8.208	1.536	1	12
HDDS Count: Total	143	9.846	1.218	6	12
HDDS Avg.: Meal	14,541	2.098	0.649	0.333	6
HDDS Avg.: Day	5,526	1.9	0.492	0.333	3.667
HDDS Avg.: Week	838	1.173	0.219	0.143	1.714
HDDS Avg.: Total	143	0.234	0.029	0.143	0.286
DSR Count: Dish	27,804	2.262	1.056	0	6
DSR Count: Meal	14,541	4.325	2.534	0	20
DSR Count: Day	5,526	11.38	5.641	0	51
DSR Count: Week	838	75.06	35.45	2	238
DSR Count: Total	143	439.8	197.0	66	1,192
Avg. Number of Dishes Prepared: Breakfast	143	1.267	0.306	1	2.833
Avg. Number of Dishes Prepared: Lunch	142	2.217	0.433	1.073	3.795
Avg. Number of Dishes Prepared: Dinner	142	2.152	0.382	1	3.447
Avg. Number of Dishes Prepared: All Meals	143	1.915	0.327	1	3.082
Number of Meals Skipped: Breakfast	143	13.18	10.08	0	39
Number of Meals Skipped: Lunch	143	5.091	8.133	0	39
Number of Meals Skipped: Dinner	143	6.594	8.168	0	38
Number of Meals Skipped: All Meals	143	25.45	23.61	0	106
Number of Times Legumes Cooked in a Day	5,526	0.187	0.39	0	1
Number of Times Legumes Cooked in a Week	838	1.235	1.493	0	7
Number of Times Legumes Cooked Total	143	7.238	6.911	0	38

Note: Summary statistics for outcome variables included in analysis presented above. $N = 143$ households, except in the cases of average number of dishes prepared for lunch and dinner. One household did not specify their cooking method for lunch and dinner dishes, despite specifying a method for breakfast dishes. Thus, this household was excluded from analyses regarding average number of dishes in a lunch or dinner meal.

Table 4: Average Treatment Effect of Solar Stove Assignment on Solar Stove Use

	Dishes Prepared Using Solar Stove			
	LPM (1)	Probit (2)	LPM (3)	Probit (4)
Solar Stove Assignment	0.444*** (0.029)	0.387*** (0.029)	0.441*** (0.028)	0.380*** (0.029)
Observations	27,804	27,804	27,804	27,804
Covariates	No	No	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.307		0.316	
Pseudo-R^2		0.364		0.375
Log Likelihood	-7795.575	-8362.790	-7620.722	-8206.375

Note: *p<0.1; **p<0.05; ***p<0.01. Estimation of coefficients for Linear Probability Model and average marginal effects for Probit model. Liang-Zeger standard errors are clustered at the household level and presented in parentheses below each effect.

Table 5: Average Treatment Effect of Solar Stove Assignment on Share of Dishes Prepared Using Solar Stove

	Share of Dishes Prepared Using Solar Stove							
	Each meal		Each day		Each week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Assignment	0.441***	0.440***	0.452***	0.450***	0.459***	0.458***	0.456***	0.454***
	(0.029)	(0.028)	(0.030)	(0.030)	(0.031)	(0.031)	(0.031)	(0.032)
Observations	14,541	14,541	5,526	5,526	838	838	143	143
Mean of Control Group	0.009	0.009	0.008	0.008	0.010	0.010	0.009	0.009
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.354	0.364	0.530	0.542	0.644	0.661	0.713	0.729

Note: *p<0.1; **p<0.05; ***p<0.01. OLS estimation of the average treatment effect of solar stove use on share of dishes prepared on a solar stove. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-6 and Eicker-Huber-White (EHW) robust standard errors are used for columns 7-8.

Table 6: Intent to Treat Effect of Solar Stove Assignment on Household Dietary Diversity Score (Count)

	Household Dietary Diversity Score (Count)									
	Dish		Meal		Day		Week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solar Stove Assignment	−0.027	−0.018	−0.032	−0.023	−0.007	−0.007	−0.004	−0.001	−0.003	−0.004
	(0.028)	(0.026)	(0.030)	(0.029)	(0.028)	(0.028)	(0.025)	(0.026)	(0.020)	(0.020)
Mean of Control Group	2.339	2.339	3.936	3.936	5.688	5.688	8.191	8.191	9.798	9.798
Observations	27,804	27,804	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	Yes	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.003	0.004	0.005	0.007	0.010	0.011	0.007	0.007	0.006	0.006

Note: *p<0.1; **p<0.05; ***p<0.01. Poisson estimation of the intent-to-treat effect of solar stove assignment on household dietary diversity scores measured as a count. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-8 and Eicker-Huber-White (EHW) robust standard errors are used for columns 9-10.

Table 7: Intent to Treat Effect of Solar Stove Assignment on Household Dietary Diversity Score (Average)

	Household Dietary Diversity Score (Average)							
	Each meal		Each day		Each week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Assignment	−0.081	−0.076	−0.014	−0.014	−0.004	−0.002	−0.001	−0.001
	(0.051)	(0.050)	(0.053)	(0.053)	(0.030)	(0.031)	(0.005)	(0.005)
Mean of Control Group	2.123	2.123	1.896	1.896	1.170	1.170	0.233	0.233
Observations	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.032	0.108	0.113	0.101	0.111	0.167	0.181

Note: *p<0.1; **p<0.05; ***p<0.01. OLS estimation of the intent-to-treat effect of solar stove assignment on household dietary diversity scores measured as an average. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-6 and Eicker-Huber-White (EHW) robust standard errors are used for columns 7-8.

Table 8: Intent to Treat Effect of Solar Stove Assignment on Dietary Species Richness

	Dietary Species Richness (Count)									
	Dish		Meal		Day		Week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solar Stove Assignment	−0.009	−0.013	0.001	0.004	0.032	0.031	0.033	0.031	0.045	0.037
	(0.035)	(0.035)	(0.051)	(0.050)	(0.058)	(0.057)	(0.067)	(0.067)	(0.070)	(0.070)
Mean of Control Group	2.255	2.255	4.282	4.282	11.09	11.09	73.04	73.04	425.91	425.91
Observations	27,804	27,804	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.008	0.009	0.028	0.029	0.071	0.073	0.144	0.149	0.207	0.226

Note: *p<0.1; **p<0.05; ***p<0.01. Poisson estimation of the intent-to-treat effect of solar stove assignment on household dietary species richness measured as a count. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-8 and Eicker-Huber-White (EHW) robust standard errors are used for columns 9-10.

Table 9: Intent to Treat Effect of Solar Stove Assignment on Average Number of Dishes Per Meal

	Number of Dishes Prepared with Solar Stove (Count)							
	All Meals		Breakfast		Lunch		Dinner	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Assignment	0.036	0.050	0.010	0.009	0.084	0.098	0.003	0.012
	(0.052)	(0.053)	(0.054)	(0.057)	(0.064)	(0.061)	(0.060)	(0.060)
Mean of Control Group	1.899	1.899	1.258	1.258	2.173	2.173	2.139	2.139
Observations	143	143	143	143	142	142	142	142
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.216	0.275	0.092	0.110	0.294	0.346	0.202	0.234

Note: *p<0.1; **p<0.05; ***p<0.01. OLS estimation of the intent-to-treat effect of solar stove assignment on the average number of dishes per meal prepared by a given household. Means are presented with associated standard errors in parentheses below. Eicker-Huber-White (EHW) robust standard errors are used for columns 1-8.

Table 10: Intent to Treat Effect of Solar Stove Assignment on Number of Meals Skipped

	Number of Meals Skipped (Count)							
	All Meals		Breakfast		Lunch		Dinner	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Assignment	−0.183	−0.140	−0.149	−0.097	−0.136	−0.072	0.025	0.025
	(0.168)	(0.170)	(0.142)	(0.142)	(0.258)	(0.260)	(0.209)	(0.209)
Mean of Control Group	27.61	27.61	14.47	14.47	5.393	5.393	6.798	6.798
Observations	143	143	143	143	143	143	143	143
Covariates	No	Yes	No	Yes	No	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.057	0.120	0.102	0.145	0.066	0.135	0.074	0.074

Note: *p<0.1; **p<0.05; ***p<0.01. OLS estimation of the intent-to-treat effect of solar stove assignment on the number of meals skipped by a household during the experiment. Means are presented with associated standard errors in parentheses below. Eicker-Huber-White (EHW) robust standard errors are used for columns 1-8.

Table 11: Intent-to-Treat Effect of Solar Stove Assignment on Total Number of Times Legume Dishes Cooked

	Total Number of Times Legume Dishes Cooked					
	Day		Meal		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)
Solar Stove Assignment	0.069	0.063	0.074	0.074	0.087	0.078
	(0.178)	(0.165)	(0.179)	(0.167)	(0.180)	(0.167)
Mean of Control Group	0.179	0.179	1.177	1.177	6.865	6.865
Observations	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.004	0.014	0.011	0.028	0.026	0.063

Note: *p<0.1; **p<0.05; ***p<0.01. Poisson estimation of the intent-to-treat effect of solar stove assignment on total number of times legume dishes were cooked. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-4 and Eicker-Huber-White (EHW) robust standard errors are used for columns 5-6.

Table 12: Local Average Treatment Effect of Solar Stove Use on Household Dietary Diversity Score (Count)

	Household Dietary Diversity Score (Count)									
	Each dish		Each meal		Each day		Each week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solar Stove Use	−0.057	−0.041	−0.077	−0.058	−0.016	−0.017	−0.009	−0.004	−0.004	−0.006
	(0.062)	(0.057)	(0.071)	(0.069)	(0.064)	(0.062)	(0.055)	(0.057)	(0.033)	(0.034)
Mean of Control Group	2.339	2.339	3.936	3.936	5.688	5.688	8.191	8.191	9.798	9.798
Observations	27,804	27,804	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. IV Poisson estimation of the local average treatment effect of solar stove use on household dietary diversity score measured as a count. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-8 and Eicker-Huber-White (EHW) robust standard errors are used for columns 9-10.

Table 13: Local Average Treatment Effect of Solar Stove Use on HDDS (Average)

	Household Dietary Diversity Score (Average)							
	Each meal		Each day		Each week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Use	−0.196	−0.184	−0.031	−0.030	−0.009	−0.003	−0.001	−0.002
	(0.124)	(0.122)	(0.119)	(0.116)	(0.064)	(0.065)	(0.008)	(0.008)
Mean of Control Group	2.123	2.123	1.896	1.896	1.170	1.170	0.233	0.233
Observations	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. IV estimation of the local average treatment effect of solar stove use on household dietary diversity scores measured as an average. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-6 and Eicker-Huber-White (EHW) robust standard errors are used for columns 7-8.

Table 14: Local Average Treatment Effect of Solar Stove Use on Dietary Species Richness

	Dietary Species Richness (Count)									
	Dish		Meal		Day		Week		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Solar Stove Use	−0.003	−0.018	0.038	0.034	0.121	0.095	0.119	0.096	0.103	0.075
	(0.078)	(0.075)	(0.125)	(0.119)	(0.146)	(0.139)	(0.078)	(0.076)	(0.123)	(0.123)
Mean of Control Group	2.255	2.255	4.282	4.282	11.09	11.09	73.04	73.04	425.9	425.9
Observations	27,804	27,804	14,541	14,541	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. IV Poisson estimation of the local average treatment effect of solar stove use on dietary species richness measured as a count. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-8 and Eicker-Huber-White (EHW) robust standard errors are used for columns 9-10.

Table 15: Local Average Treatment Effect of Solar Stove Assignment on Average Number of Dishes Per Meal

	Average Number of Dishes Per Meal							
	All Meals		Breakfast		Lunch		Dinner	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Use	0.062		0.016	0.016	0.143	0.166*	0.005	0.020
	(0.087)		(0.090)	(0.092)	(0.106)	(0.099)	(0.099)	(0.097)
Mean of Control Group	1.899	1.899	1.258	1.258	2.173	2.173	2.139	2.139
Observations	143	143	143	143	142	142	142	142
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. IV OLS estimation of the local average treatment effect of solar stove use on the average number of dishes per meal prepared by a given household. Means are presented with associated standard errors in parentheses below. Eicker-Huber-White (EHW) robust standard errors are used for columns 1-8.

Table 16: Local Average Treatment Effect of Solar Stove Use on Number of Meals Skipped

	Number of Meals Skipped (Count)							
	All Meals		Breakfast		Lunch		Dinner	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Stove Use	−0.353	−0.261	−0.267	−0.183	−0.487	−0.302	−0.039	−0.039
	(0.232)	(0.235)	(0.219)	(0.227)	(0.348)	(0.372)	(0.311)	(0.311)
Mean of Control Group	27.61	27.61	14.47	14.47	5.393	5.393	6.798	6.798
Observations	143	143	143	143	143	143	143	143
Covariates	No	Yes	No	Yes	No	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. OLS IV estimation of the local average treatment effect of solar stove use on the count of meals skipped by a household during the experiment. Means are presented with associated standard errors in parentheses below. Eicker-Huber-White (EHW) robust standard errors are used for columns 1-8.

Table 17: Local Average Treatment Effect of Solar Stove Assignment on Total Number of Times Legume Dishes Cooked

	Total Number of Times Legume Dishes Cooked					
	Day		Meal		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)
Solar Stove Use	0.261	0.025	0.272	0.040	0.215	0.040
	(0.380)	(0.318)	(0.393)	(0.327)	(0.274)	(0.237)
Mean of Control Group	0.179	0.179	1.177	1.177	6.865	6.865
Observations	5,526	5,526	838	838	143	143
Covariates	No	Yes	No	Yes	No	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: *p<0.1; **p<0.05; ***p<0.01. Poisson estimation of the local average treatment effect of solar stove use on total number of times legume dishes were cooked. Means are presented with associated standard errors in parentheses below. Liang-Zeger cluster-robust standard errors are clustered at the household level for columns 1-4 and Eicker-Huber-White (EHW) robust standard errors are used for columns 5-6.

APPENDIX A

Descriptive Tables

Table A1: Frequency of Food Group Consumption

Food Group	Frequency	Percent	Cumulative Percent
Cereals	26,395	32.77	32.77
Vegetables	13,238	16.435	49.21
Oils & Fats	10,125	12.57	61.78
Tubers	6,730	8.355	70.13
Leafy Greens	6,696	8.313	78.44
Legumes & Nuts	4,213	5.23	83.67
Fish	3,869	4.803	88.48
Spices & Condiments	3,593	4.461	92.94
Milk	1,805	2.241	95.18
Vitamin-A Vegetables	1,153	1.431	96.61
Flesh Meat	1,095	1.359	97.97
Beverages	931	1.156	99.13
Eggs	332	0.412	99.54
Fried Snacks	178	0.221	99.76
Fruits	131	0.163	99.92
Organ Meat	29	0.036	99.96
Vitamin-A Fruits	17	0.021	99.98
Sweets	12	0.015	99.99
None	5	0.006	100.00
Total	80,547	100	100.00

Note: Tabulation of the frequency of food groups to which ingredients used in meal preparation belong.

Table A2: Frequency of Ingredient Consumption

Ingredient	Frequency	Percent	Cumulative Percent
Porridge	10,601	13.16	13.16
Oil	9,897	12.29	25.45
Maize	8,316	10.32	35.77
Tomato	8,021	9.958	45.73
Maize Flour	6,143	7.627	53.36
Cassava	5,639	7.001	60.36
Fish	3,869	4.803	65.16
Onion	3,800	4.718	69.88
Sugar	2,687	3.336	73.22
Rape	2,105	2.613	75.83
Groundnut	1,969	2.445	78.27
Sour Milk	1,502	1.865	80.14
Cowpea	1,326	1.646	81.79
Cassava Leaves	1,073	1.332	83.12
Sweet Potato	1,030	1.279	84.40
Pumpkin Leaves	1,009	1.253	85.65
Amaranth	984	1.222	86.87
Hibiscus	944	1.172	88.04
Rice	873	1.084	89.13
Meat	827	1.027	90.15
Total	80,547	100	100

Note: Frequency tabulation of the top 20 ingredients used by participants for meal preparation.

Table A3: Frequency of Processing Levels

Level of Processing	Frequency	Percent	Cumulative Percent
Unprocessed	49,632	61.62	61.62
Processed Ingredient	19,485	24.19	85.81
Proccessed Food	10,773	13.38	99.18
Ultra-Processed	657	0.82	100.00
Total	87,973	100.00	100.00

Note: Frequency tabulation for each of the four levels of ingredient processing specified by the FAO.

Table A4: Final Outcomes: Decision Rules

Outcome Variable	H_1
Household Dietary Diversity Score (Average)	$\mu > 0$
Household Dietary Diversity Score (Count)	$\mu > 0$
Dietary Species Richness (Count)	$\mu > 0$
Total Number of Dishes in a Meal	$\mu > 0$
Total Meals Skipped (Count)	$\mu < 0$

Note: Table lists each decision rule for final outcome alternative hypotheses (H_1).

Table A5: Definitions of Variables Used in Empirical Analysis

Variable	Description
Solar Stove Assignment	Random assignment of solar stove to household (=1 if assigned a stove)
Solar Stove Use	Use of solar stove to prepare dish (=1 if used stove)
Age	Age of household head in years
Cloud Cover	Percentage of cloud cover
Education	Education of household (None = 0, Primary = 1, Secondary = 2, Higher = 3)
Gender	Gender of household head (=1 if participant identifies as female)
Household Dietary Diversity Score (Dish)	Dish-level measure of dietary diversity. Potential range: 1 - 6
Household Size	Total number of individuals in the household
Tropical Livestock Index	Tropical Livestock Unit/250 kg live weight
Village	Village fixed effect
Group	Aquatic and Agricultural Systems Group
Household Dietary Diversity Score	The food groups associated with the ingredients a household includes in a given dish, measured as both an average or a total count. Also aggregated to the meal, day, week, and overall (six-week) levels.
Dietary Species Richness Score	The total count of species associated with the ingredients a household includes in a given dish. Aggregated to the meal, day, week, and overall (six-week) levels.
Avgerage Number of Dishes Prepared	The average number of dishes a household includes prepares for a given meal over the six-week experimental time period. Calculated for breakfast, lunch, dinner, and overall meals.
Number of Meals Skipped	The total number of meals a household skips over the six-week experimental time period. Calculated for breakfast, lunch, dinner, and overall meals.
Number of Times Legumes Cooked	The number of times a household prepares a legume dish for a meal. Aggregated to the day, week, and six-week experimental time period.

Note: Covariates and main independent variables included in analysis are presented in the top section, with outcome variables presented below.

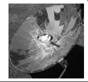
APPENDIX B

Experimental Food Diaries

Figure B1: Daily Food Diary, Days 1-3

Libizo la ba batalima sitofu:
Lizazi lakukala: dd/mm/yy
Lizazi lamakalelo la kumipotela: dd/mm/yy
Lizazi la bubeli la kumipotela: dd/mm/yy
Lizazi la mafelelezo: dd/mm/yy

Sitofu sa lizazi **(S)**



Likota **(F)**

Mashala **(C)**

Masu **(M)**

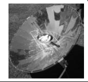
	Sunda 1	**Mukushuko wa kakusasani**				**Mukushuko wa musihali**				**Mulalelo**				Mu biliselize fa teñi hakai mezi kapa mabisi kachenu		**FonomuapeheS-F-C-M**	**Lt/CC**
		Libizo za lico				Libizo za lico				Libizo za lico							
	Zetokwahala	1	2	3	4	1	2	3	4	1	2	3	4				
DAY 1	1													1			
	2													2			
	3													3			
	4													4			
	5													5			
	6													6			
	Fonomuapehe S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																
DAY 2	Zetokwahala													1			
	1													2			
	2													3			
	3													4			
	4													5			
	5													6			
	6													7			
	Fonomuapehez S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																
DAY 3	1													1			
	2													2			
	3													3			
	4													4			
	5													5			
	6													6			
	Fonomuapehe S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																

Note: Participating households logged each ingredient in each dish for each meal (classified as breakfast, lunch, or dinner) throughout the six-week experiment. Participants also logged the cooking method (solar stoves, firewood, charcoal, or dung, pictured at the top of the diary) for each dish. Time and money spent on fuel collection and purchases were logged weekly.

Figure B2: Daily Food Diary, Days 4-6

Libizo la ba batalima sitofu:
Lizazi lakukala: dd/mm/yy
Lizazi lamakalelo la kumipotela: dd/mm/yy
Lizazi la bubeli la kumipotela: dd/mm/yy
Lizazi la mafelelezo: dd/mm/yy

Sitofu sa lizazi **(S)**



Likota **(F)**

Mashala **(C)**

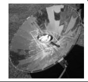
Masu **(M)**

	Sunda 1	**Mukushuko wa kakusasani**				**Mukushuko wa musihali**				**Mulalelo**				Mu biliselize fa teñi hakai mezi kapa mabisi kachenu		**FonomuapeheS-F-C-M**	**Lt/CC**
		Libizo za lico				Libizo za lico				Libizo za lico							
	Zetokwahala	1	2	3	4	1	2	3	4	1	2	3	4				
DAY 4	1													1			
	2													2			
	3													3			
	4													4			
	5													5			
	6													6			
	Fonomuapehe S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																
DAY 5	Zetokwahala													1			
	1													2			
	2													3			
	3													4			
	4													5			
	5													6			
	6													7			
	Fonomuapehez S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																
DAY 6	1													1			
	2													2			
	3													3			
	4													4			
	5													5			
	6													6			
	Fonomuapehe S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																

Note: Participating households logged each ingredient in each dish for each meal (classified as breakfast, lunch, or dinner) throughout the six-week experiment. Participants also logged the cooking method (solar stoves, firewood, charcoal, or dung, pictured at the top of the diary) for each dish. Time and money spent on fuel collection and purchases were logged weekly.

Figure B3: Daily Food Diary, Day 7

Libizo la ba batalima sitofu:
Lizazi lakukala: dd/mm/yy
Lizazi lamakalelo la kumipotela: dd/mm/yy
Lizazi la bubeli la kumipotela: dd/mm/yy
Lizazi la mafelelezo: dd/mm/yy

Sitofu sa lizazi **(S)**

Likota **(F)**

Mashala **(C)**

Masu **(M)**


	Sunda 1	**Mukushuko wa kakusasani**				**Mukushuko wa musihali**				**Mulalelo**				Mu biliselize fa teñi hakai mezi kapa mabisi kachenu		**FonomuapeheS-F-C-M**	**Lt/CC**
		Libizo za lico				Libizo za lico				Libizo za lico							
	Zetokwahala	1	2	3	4	1	2	3	4	1	2	3	4				
DAY 7	1													1			
	2													2			
	3													3			
	4													4			
	5													5			
	6													6			
	Fonomuapehe S-F-C-M													8			
	Haeba nemulibezi?													9			
	Tuñolo: Haeba nu hapeile fateni manawa, muñole fo noakuma kapa likomoki ze nomu hapeile																

Mifuta ye mimu yemuitusisanga fa kusokela,ki bomani baba mitusanga kwa ku lwalela likota mwa lapa yamina

	Likota / Masu					**Mashala**			
Likota mashala masu	Libizo la munga ndu kappa yaile kwa kulwalela likota/masu	Konobaizo lwalela likota/masu - teko	Nako yeneile kwa kulwalela likota/masu	Zekuma kai	Ha kai mwa sunda	Kiufi wa lubasi yana zusize mashala	Yakuleka kwa musika kapa ku mut (cwalo cwalo)	Mulekile yakuma kai (kg)	Ha kai mwa sunda

Note: Participating households logged each ingredient in each dish for each meal (classified as breakfast, lunch, or dinner) throughout the six-week experiment. Participants also logged the cooking method (solar stoves, firewood, charcoal, or dung, pictured at the top of the diary) for each dish. Time and money spent on fuel collection and purchases were logged weekly.

APPENDIX C

Cloud cover calculation

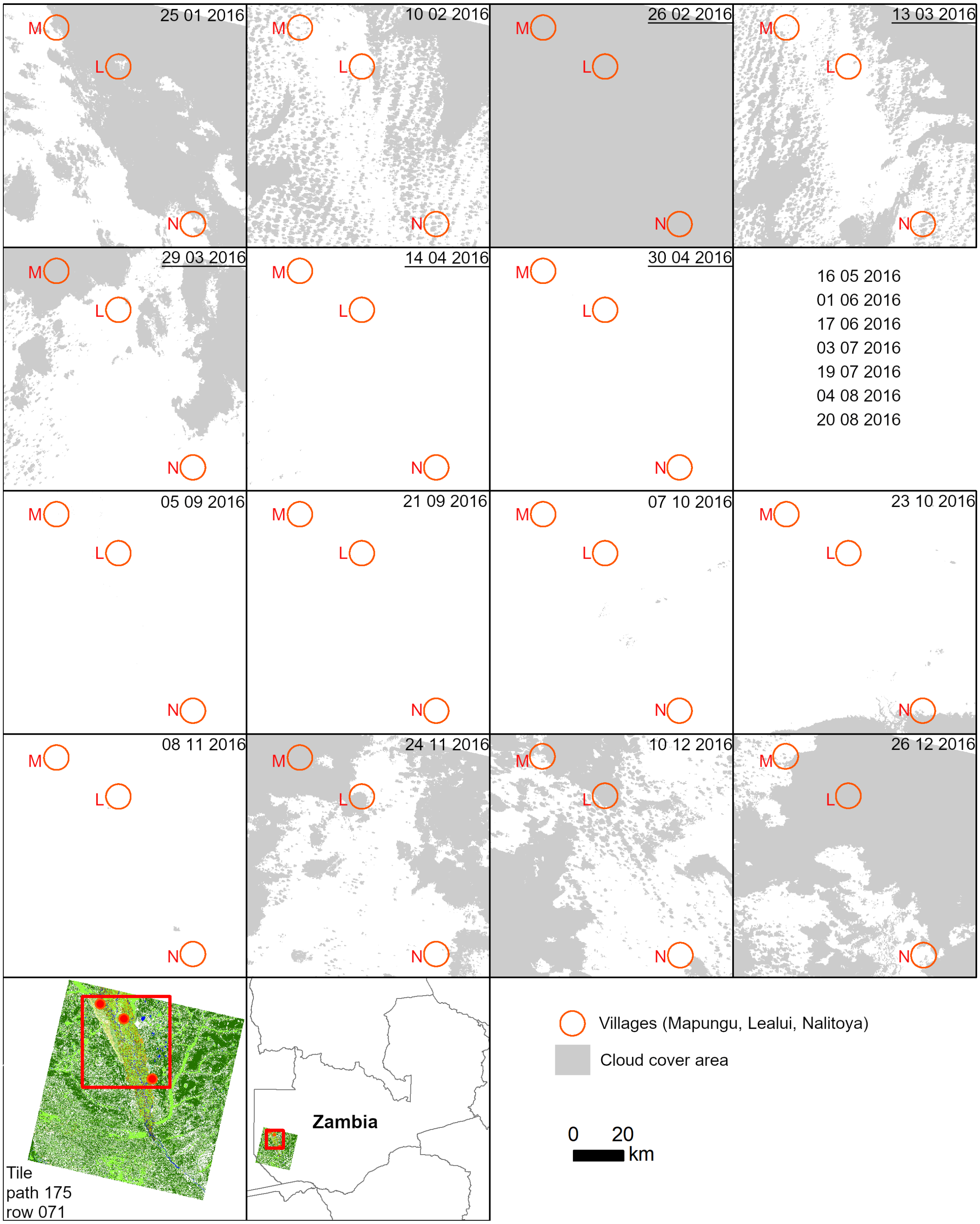
We used the Landsat Collection 1 Level-1 band Quality Assessment band (BQA) from imagery taken throughout the year 2016 (tile path 175; row 071). We reclassified the pixels on the BQA with high cloud or cloud shadow confidence attributes as 1/cloud cover to delimit the cloud area. Pixels with other attributes (e.g., low or medium confidence) were reclassified as 0/no cloud cover. We calculated the cloud area in a 5km radius around each village (Table C1 and Figure C1) for the relevant week.

Table C1: Percentage of village area with clouds or cloud shadows

Data Aquired			Villages			Project
Month	Day	Year	Mapungu	Lealui	Nalitoya	Ongoing
1	25	2016	58.0	91.5	25.2	No
2	10	2016	13.6	5.69	28.8	No
2	26	2016	100	100	100	Yes
3	13	2016	11.8	1.70	35.8	Yes
3	29	2016	100	2.06	0.00	Yes
4	14	2016	0.00	0.00	0.00	Yes
4	30	2016	0.00	0.01	0.00	Yes
5	16	2016	0.00	0.00	0.00	No
6	1	2016	0.00	0.00	0.00	No
6	17	2016	0.00	0.00	0.00	No
7	3	2016	0.00	0.00	0.00	No
7	19	2016	0.00	0.00	0.00	No
8	4	2016	0.00	0.00	0.00	No
8	20	2016	0.00	0.00	0.00	No
9	5	2016	0.10	0.00	0.00	No
9	21	2016	0.00	0.12	0.00	No
10	7	2016	0.00	0.00	0.00	No
10	23	2016	0.00	0.00	33.5	No
11	8	2016	0.00	0.00	0.00	No
11	24	2016	99.9	54.1	1.46	No
12	10	2016	53.8	91.0	0.88	No
12	26	2016	26.9	100	23.8	No

Note: Percentage of the area in a buffer of 5km around each village with clouds or clouds shadows. See figure 1 for visual identification of the cloud cover area throughout the year 2016.

Figure C1: Cloud cover during experiment

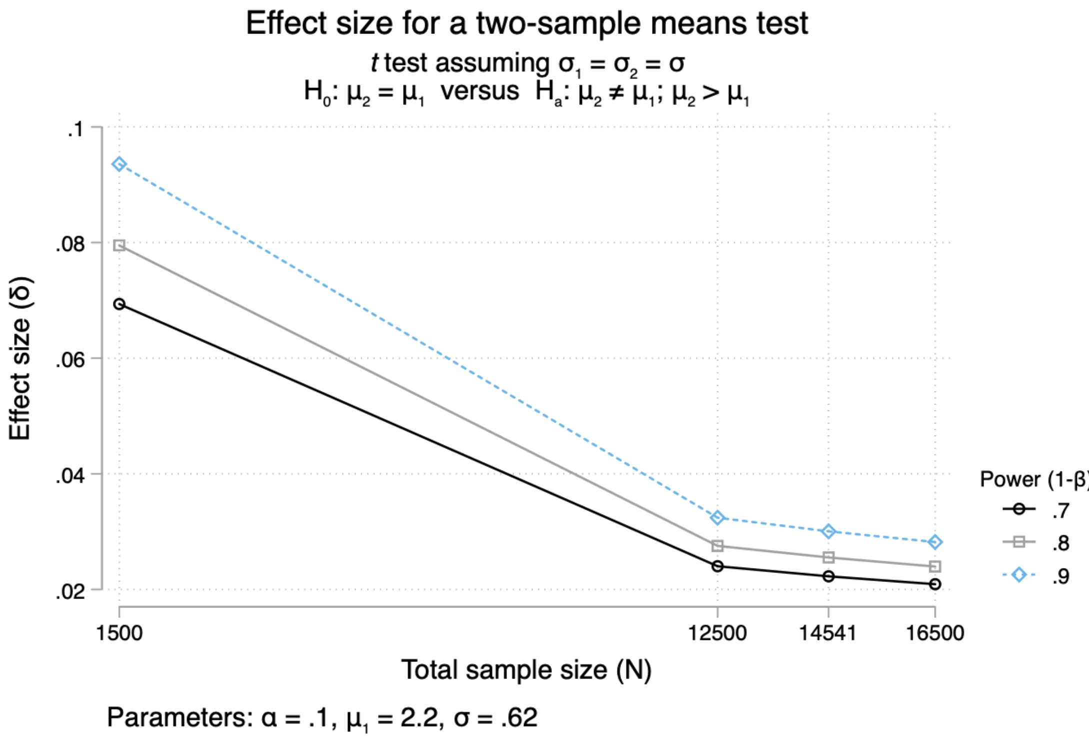


Note: Cloud cover area delimited with Landsat 8 Enhanced Thematic Mapper path 175 row 071 in a radius of 5km around each village where the solar project took place during the end of February until the end of April 2016. The whole tile area had had a cloud cover of 0% from 16 05 2016 until 20 08 2016.

APPENDIX D

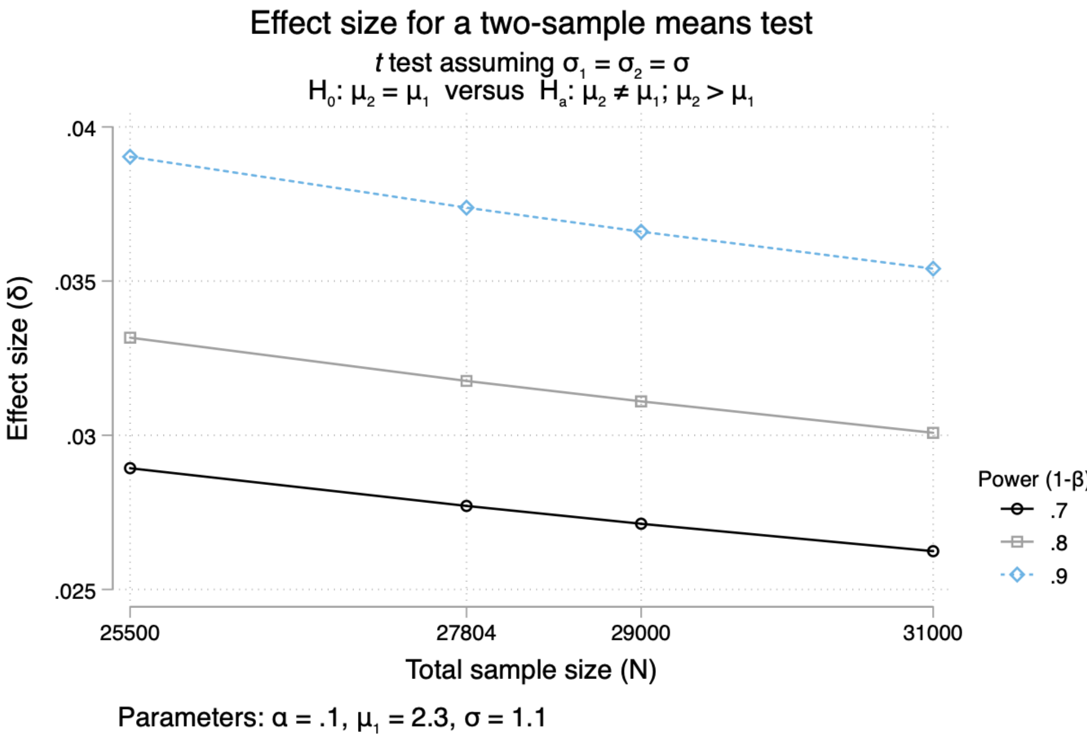
Power Calculations

Figure D1: Power Calculation: HDDS Average, Meal



Note: Power calculation graphic for household dietary diversity score calculated as an average at the meal level. The gray (middle) line indicates that at 14,541 observations, the minimum detectable treatment effect would have a magnitude of roughly 0.025. Since our measured treatment effect is -0.081, we know that our results are truly non-significant results and are not biased from our sample size.

Figure D2: Power Calculation: DSR Count, Dish



Note: Power calculation graphic for dietary species richness calculated as a count at the dish level. The gray (middle) line indicates that at 27,804 observations, the minimum detectable treatment effect would have a magnitude of roughly 0.032. Since our measured treatment effect is -0.003, we know that our results are underpowered and may not provide reliable estimates of null results.

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