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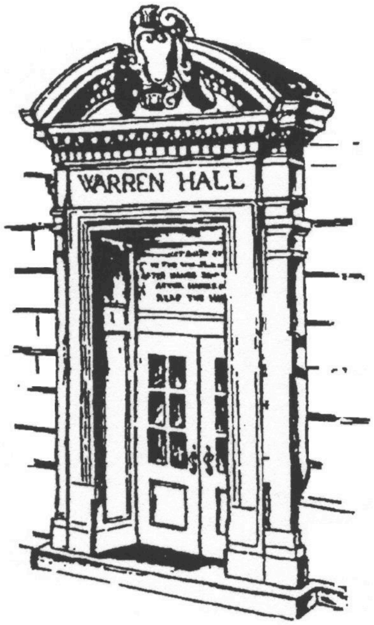
September 2014



Working Paper

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What is a "Meal"? Comparing Methods Of Auditing Carbon Offset Compliance for Fuel Efficient Cookstoves

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What is a "Meal"? Comparative Methods of Auditing Carbon Offset Compliance for Fuel Efficient Cookstoves

Stephen Harrell[a], Theresa Beltramo[b], Garrick Blalock[c], David I. Levine[d], Andrew M. Simons[c, *]

Smoke from inefficient biomass cookstoves contributes to global climate change and kills approximately four million people per year. Credits for reduced carbon emissions can potentially subsidize fuel-efficient cookstoves that reduce these harms. Understanding the accuracy of different methods to monitor stove usage is necessary to accurately target carbon credits and, thus, to curtail the environmental and health damages from inefficient stoves. This paper compares five methods of measuring stove usage: stove usage monitors that continuously log stove temperature; enumerators' observations of cooking; household food diaries, weighing fuel; and household air pollution using mean 24 hour concentrations of particulate matter. We find statistically significant positive correlations between almost all pairs of measures. While the correlations are positive, the explanatory power of each measure for another is weak. The weak correlations emphasize the importance of using multiple measures to audit the changes in stove use and related carbon offsets.

Keywords: carbon credits; carbon emissions; biomass cookstoves; biomass fuel; monitoring and evaluation; stove use monitor

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1. Introduction

Globally, more than three billion people cook on inefficient stoves that burn solid fuels such as wood and charcoal (Martin II et al. 2011). Inefficient cookstoves contribute to global climate change and deforestation (Arnold, Köhlin, and Persson 2006; Ramanathan and Carmichael 2008). Thus, some stove projects have received carbon credits that subsidize efficient stoves (Simon, Bumpus, and Mann 2012). Efficient cookstoves are an especially attractive target for carbon credits because stoves also improve the health, economic prospects, and safety of users. Fuel-efficient cookstoves can improve health by reducing the household air pollution that leads to an estimated 4 million deaths a year (Nigel Bruce et al. 2007; Ezzati and Kammen 2002; McCracken et al. 2007; Smith et al. 2010; Smith-Sivertsen et al. 2009; Lim et al. 2012). Fuel-efficient cookstoves can also reduce the time people (usually women and children) spend collecting fuel (Kammen, Bailis, and Herzog 2002).

To quantify the benefits of efficient cookstoves, it is not enough to measure the usage of the efficient stove. It is crucial to measure both use of the new stove *and* any reduction in use of traditional stoves (Ruiz-Mercado et al. 2011; Miller and Mobarak 2013). Many owners of new stoves continue to use old stoves and fuels in a phenomenon known as "stove stacking," which reduces the benefits from using efficient cookstoves. The carbon market needs to know if new stoves deserve credits for lower emissions.[1]

[1] For more details, see http://www.cdmgoldstandard.org/frequently-asked-questions/carbon-market.

This paper focuses on understanding stove use in a variety of ways. We measure how five different measures of cooking correlate across 163 households. We use measures from stove usage monitors that continuously log stove temperatures, enumerator observation of cooking, detailed household food diaries, weight of wood used, and household air pollution (PM 2.5) concentrations. We do this analysis both across and within households.

Our goal is to identify how well these measures predict each other. If some measures correlate strongly with others, then carbon offset auditors can rely on only a subset of measures (or perhaps a single measure). If an inexpensive method's results strongly predict a more costly method's results, perhaps the inexpensive method can be used and reduce monitoring costs. Conversely, if one measure appears unrelated to the other measures, then it may not be valid and should not be used in isolation. If, as we find, all of the measures correlate positively, but all of the correlations are weak, then carbon compliance officers and related researchers must continue to improve measurement techniques. Until that time, multiple measures will be necessary to create confidence in stove use metrics and their related quantity of carbon offsets.

1.1 Measuring stove usage

The first of our five usage measures is stove usage monitors (SUMs) that continuously record stove temperature data. The temperature data is then processed with an algorithm to determine usage of each stove in a household (Ruiz-Mercado et al. 2013; Ruiz-Mercado et al. 2008; Simons et al. 2014). SUMs offer an unobtrusive, precise, relatively inexpensive, and objective measure of stove usage. Given that the goal of auditing for carbon offsets is to compare the carbon released by households before and after the introduction of a fuel efficient stove, the development of algorithms for SUMs temperature data for three stone fires and fuel efficient stove types could allow for longer periods of comparison (i.e., months) compared to kitchen performance tests—that measure kilograms of wood used—which usually last a week or less. However, a concern with SUMs is that they record temperature, not stove usage. In a companion paper (Simons et al. 2014) we discuss the many slippages between temperature and cooking.

A second way to measure stove use is to directly observe it. Enumerators were instructed to mark whether a household was using a stove (on/off) and which stove was being cooked with (three stone fire/fuel efficient stove) whenever they entered a study participant's home. This directly measures use, but since enumerators do not stay present in a house for long periods of time they cannot observe all stove usage. Combining visual observations of stove use with SUMs temperature data improves the ability to measure usage of traditional stove types such as three stone fires (Simons et al. 2014).

Food diaries are a third option to understand populations' diets and cooking practices (Prentice 2003; Krall and Dwyer 1987). While food diaries create a detailed accounting of everything cooked in a given household, they can be inaccurate due to recall bias and experimenter demand effects (if respondents over-report use of stoves or foods that the experimenter is interested in). Food diaries also do not directly measure the duration of cooking (although they can include proxies by understanding the average time for common dishes cooked and/or which stoves are used for cooking). One potential complexity with self-reported food diaries is households cooking two meals at once, but then reporting the two meals as separate events. Coupling food diaries with other measurements may help with understanding the meaning and validity of food diaries.

A kitchen performance test (KPT) measures the woodpile in a kitchen on sequential days to quantify the amount of wood used in a given 24-hour period.[2] The KPT is the primary method used to calculate carbon credits for a stove project (The Gold Standard Foundation 2013). To minimize variance, the standard recommendation is that the KPT testing period should be at least three days, avoiding weekends and holidays (Smith et al. 2007). Although the KPT is a useful tool to measure fuel consumption, it is imperfect. Changes in the weight of a wood pile may not equal wood burnt due to households sharing wood with neighbors, households inadvertently adding wood to the measured pile of wood, or wood becoming wet or dry between initial and final weighing. Additionally, direct observational processes alter participants' behavior (as noted by (Ezzati, Saleh, and Kammen 2000; Smith-Sivertsen et al. 2009; Simons et al. 2014)).

Another measurement method used to ascertain household air pollution levels in cookstove studies is mean 24-hour concentrations of particulate matter (PM). PM monitors measure the concentration of particles in wood smoke that have negative health effects

[2] For details, see http://ehs.sph.berkeley.edu/hem/content/KPT_Version_3.0_Jan2007a.pdf.

(McCracken et al. 2007; Smith et al. 2010). However, PM data is an imperfect proxy for cooking because PM concentration potentially depends on stove type, fuel, cooking practice (high or low temperature, smoldering wood, etc.), airflow in the kitchen, moisture content of wood, proximity of cook to the fire, and other factors.

1.2 Prior studies comparing measures of stove usage

A few studies compare different methods for measuring usage or how the impacts of health and fuel correlate with usage (Ruiz-Mercado et al. 2013; N. Bruce et al. 2006). Most past studies have used one or two methods to determine improved stove usage and impacts. Environmental health scientists have long been concerned with cross-verification of household air pollution using PM and CO measure concurrently in households. For example, (Smith et al. 2010) compared PM concentrations with CO concentrations. (Ruiz-Mercado et al. 2013) compared time spent cooking (using SUMs) with food diaries. Our study is unique in that it compares five methods of stove measurement: SUMs temperature data, direct visual observation, food diaries, kitchen performance tests (kilograms of wood used), and household air pollution (mean 24 hour concentrations of particulate matter).

1.3 Cooking Practices in our Study Area

We selected the Mbarara region because it is rural, almost all families cooked on a traditional three-stone fire, there was no active fuel efficient cookstove intervention in the region, it was less than a day's travel from Kampala, and families spent a lot of time gathering wood.[3] The main economic activity is agrarian including farming of *matooke* (a type of green banana), potatoes, and millet as well as raising livestock. Almost all families cook on a traditional three-stone fire, usually located within a cooking hut. In our sample 62% of households had no windows in the cooking hut, while 38% had one or more windows.

There are four main meals cooked in the study zone: breakfast, lunch, afternoon tea, and dinner. Common breakfast meals cooked include milk, tea, and maize porridge. Households cook breakfast 81% of the time, cooking on average for 5.4 people. Common lunch meals include *matooke* and beans. Households cook lunch 89% of the time, cooking on average for 5.3 people. Common afternoon tea meals include tea and milk. Households cook afternoon tea 69% of the time cooking for an average of 4.4 people. Common dinner meals include matooke and beans. Households cook dinner 96% of the time, cooking on average for 6.1 people. Most stove usage occurs during lunch and dinner preparation, with *matooke* and beans as the most common and most time-consuming foods cooked. *Matooke*, the main food for lunch and dinner, is typically steamed for 3–5 hours. Beans, another common food, are prepared by boiling and simmering for 2–4 hours.

[3] Wood was scarcer in some northern parts of Uganda, but those districts proved too far of a distance with poor road infrastructure for us to work in.

2. Methods

To study the demand for and effects of efficient stoves, we sold wood-burning Envirofit G3300 stoves in the region. The results of the impact of the Envirofit G3300 stove on health, fuel use, and behavior change are the focus of a subsequent study. We held 14 parish-level sales meetings where we offered the Envirofit stove.[4] We asked households that decided to purchase the stove if they would be willing to participate in a stove usage study in which usage of the three-stone fire would be compared with usage of the Envirofit stove. Households were eligible to participate in the study if they mainly used wood as a fuel source, regularly cooked for eight or fewer persons (the Envirofit is able to cook Ugandan-size portions for at most eight people), someone was generally home every day, and cooking was largely in an enclosed kitchen. Of the eligible buyers, we randomly chose 12 households per parish to participate in the stove usage study, resulting in a total of 168 participants across 14 parishes. The study took place from March through September of 2012.

In this paper we analyze data from the baseline measurement period. During the baseline measurement period, enumerators visited households once a day for four days, yielding three 24-hour periods of measurement. During each 24-hour period of measurement we recorded temperatures on each stove every 30 minutes using Stove Usage Monitors (SUMs); physical observations of stoves in use; food diaries consisting of foods cooked, type of fuel(s) used, type(s) of stove(s) used, number of stoves used, and number of people

[4] A parish is an administrative unit that covers a handful of villages and typically has about 5000–6300 residents.

cooked for each meal; the amount of fuel used via Kitchen Performance Tests (KPTs); and mean 24-hour particulate matter concentrations of $PM_{2.5}$ using University of California, Berkeley Particle and Temperature Sensors (UCB-PATS).

The SUMs used for our project, iButtons™, manufactured by Maxim Integrated Products, Inc., are small stainless steel temperature sensors about the size of a small coin and the thickness of a watch battery which can be affixed to a stove, three-stone fire, or open fire and record temperatures with an accuracy of +/- 1.3 °C up to 85 °C.[5] The SUMs were set to record temperatures every 30 minutes. We placed one SUM on each three-stone fire, as three-stone fires comprised 97% of the traditional stoves in our study area.[6] The vast majority of households (97%) use two three-stone fires to cooks meals. Typically, households have one larger three-stone fire to cook the main part of the meal (usually *matooke* and/or beans), and a smaller three-stone fire to cook side dishes and sauces. In these instances we placed one iButton on each three-stone fire. Approximately every 4–6 weeks we collected the SUMs, downloaded the temperature data, and replaced them with new SUMs. For a more detailed description of the data collection process with SUMs see (Simons et al. 2014).

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[5] For additional details concerning the SUMs devices see the product description website at: http://www.berkeleyair.com/products-and-services/instrument-services/78-sums.

[6] Due to the extremely small sample sizes of mud stoves (2%) and charcoal stoves (1%) in the study area, the analysis only covers three-stone fires.

Enumerators recorded visual observations of stoves in use each time they visited a household. Throughout the experiment, every time an enumerator entered a home he or she visually assessed if a given stove was in use based on the appearance of a flame or hot coals and food being cooked. The individual SUMs readings were matched based on date and timestamp to the visual (on/off) observations of stove use. Then we used a logistic regression to predict the probability a given stove is in use based on the temperature readings from the SUMs devices (Simons et al. 2014).

For the kitchen performance test (KPT) we recorded detailed food diaries and measured wood use for three consecutive days, starting Tuesday and ending Friday, and following best practice, avoiding weekends and holidays (Smith et al. 2007). Households listed the foods cooked, fuels used and number of people cooked for each meal in the last 24 hours in their food diaries. In addition, households reported any special event in the last 24 hours (for example, a large party).

On the initial visit, the data collection team asked the household cook to describe what fuels they would use in the next 24-hour period. To ensure that the household did not run out of fuel the household was asked to add a few extra pieces. In the event that the household did not have enough wood, the data collection team would offer a few pieces of wood, but instructed households that they should prepare to have enough wood for the remaining visits. In approximately 24 hours, the data collection team returned and weighed the remaining fuel. Although the team attempted to return to households in exactly 24 hours, the exact time varied. In the end 96% of visits were between 20.4 and 27.6 hours of the previous visit. We aligned the SUMs data and PM measures to use the actual KPT measurement period as one day of measurement.

To measure kitchen level exposure to household air pollution, we measured mean 24 hour concentrations of $PM_{2.5}$ by installing UCB-PATS PM monitors in study participants' homes during the same 72 hours of the kitchen performance test. We followed best practices as outlined by Berkeley Air Monitoring Group and measured three consecutive days of mean 24 hour $PM_{2.5}$ concentrations in the kitchen. The PM monitors $PM_{2.5}$ refers to particulate matter with a diameter of less than or equal to 2.5μm and the UCB-PATS PM monitors were used to generate mean 24 hour average PM2.5 readings in μg/m^3. Notably, these ambient concentration readings alone could mask individuals' true exposure, as exposure may also vary with an individual's proximity to the stove during periods when the stove is in use (Duflo, Greenstone, and Hanna 2008).

2.1 Statistical Methods

We compared each of the cooking event measurements by using pooled (ordinary least squares) and within household (fixed effects) regressions. Pooled regressions were clustered by household. Within household estimators eliminate the bias of time-invariant omitted variables (e.g., ventilation, altitude, etc.) by including a household fixed-effect. However, because the within-household estimations only consider changes in covariates over time, our identifying variation is very limited and likely attenuates our point estimates downward. We ran OLS regressions with the following specification:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it}$$

Here Y_{it} is a cooking measure (time spent cooking, wood use, or PM) at household i on day t, the X_{jit} (j=1 or 2) are alternative cooking measures (# of meals cooked, cooked matooke or beans, number of people cooked for, or one of the other cooking measures), and u_{it} is a residual for that household that day.

We also ran regressions with a fixed effect for each household (vi):

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + v_i + \varepsilon_{it}$$

The coefficients β_1 and β_2 estimate how increasing one measure of stove usage at a household predicts higher levels of another measure of stove usage at that household on a different day that week. The fixed effects estimator has the advantage that fixed attributes of the home that week (e.g., ventilation or placement of the SUM) do not affect the estimate. The disadvantage is that it relies only on within-household variation across 3 or so measurement days. Thus, its precision will be low if households do not change their measured behavior much across adjacent days.

3. Results and Discussion

3.1 Descriptive Statistics

Table 1 includes summary statistics for minutes cooked based on the predicted logit specification for the selected days of the kitchen performance tests. These statistics correspond to the predicted stove usage for the 219 24-hour periods when we also had wood weighing and food diaries. Of these days, the main three-stone fire was used on average for 9 hours and the secondary three-stone fire was used on average for 6 hours and 40 minutes.

Over the baseline measurement period of 391 days respondents reported cooking an average of 3.34 meals per day (Table 1). Most stove usage occurs during preparation of the two largest meals—lunch and dinner; thus the analysis focuses on these two meals. The most common meals cooked for lunch and dinner are matooke and beans. For lunch, matooke was cooked on 78% of days and beans were cooked on 42% of days. For dinner, matooke was cooked on 71% of days and beans were cooked on 56% of days. Matooke or beans were cooked for either lunch or dinner 97% of the time (Table 2).

The maximum number cooked for lunch or dinner had an average of 6.34 people. Snack/Tea has the lowest average number of attendees—4.4—while dinner has the largest—6.1 people.

Wood weights were taken over three twenty-four hour periods at each household, resulting in a total of 359[7] measures of daily wood weights. Mean daily wood use is 9.90 kilograms (Table 1). After top-coding the highest 5%, the mean amount of wood used in a 24-hour period was 9.09 kilograms.

There are 366 days of particulate matter concentrations measurements with a mean 24-hour average PM concentration of 1019 μg/m^3. This is well above U.S. E.P.A's recommended maximum mean 24-hour concentration of 35 μg/m^3.[8]

3.2 Regression Analyses

We first examine how well the number of lunch or dinner meals cooked (based on self-reported food diary data) predicts time spent cooking, as measured by our Stove Usage Monitors (Table 4).[9] In the pooled regression, households cooking lunch or dinner predict 5.5 more hours of stove use (95% confidence interval 2.8 to 8.3, col. 1). This point estimate is 53% of a standard deviation and about 35% of the mean of hours cooked. Although the coefficient is large, the R^2 is only 4.3%.

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[7] There are 376 measures of wood weights, but we dropped 17 negative values (4.5% of the data). The likely cause of these negative values is that the household added wood to the wood pile before it was weighed the following day.

[8] See http://www.epa.gov/air/criteria.html for details.

[9] Recall that our stove usage metrics generated from SUMs temperature data incorporates visual observations of stove use in the algorithm to convert temperatures to stove usage.

When we include a fixed effect for each household (col. 2), the estimate implies that on days a household cooked lunch or dinner, the household cooked 2.0 hours longer than normal (95% CI = 0.1 to 3.9).

When we include instances of cooking beans or matooke for lunch or dinner (col. 3 and col. 4), we find no statistically significant correlation with time spent cooking. When we include the maximum number of people cooked for lunch or dinner, we find that cooking for one additional person results in a 0.7-hour increase in stove use (95% confidence interval 0.1 to 1.3, col. 5).

We next examine how well the number of lunch or dinner meals cooked (based on self-reported food diary data) predicts kilograms of wood use (Table 5). In the pooled regression households cooking lunch or dinner predicts a 1.8-kilogram increase in wood used (95% confidence interval 0.3 to 3.2, col. 1). This point estimate is 40% of a standard deviation and about 20% of the mean of wood use. Although the coefficient is fairly sizable, the R^2 is only 2.2%.

When we include the number of instances of cooking beans or matooke for lunch or dinner (col. 3 and col. 4), we find no statistically significant correlation with the weight of wood used. When we include the maximum number of people cooked for lunch or dinner, cooking for one additional person results in a 0.5 kg increase in wood use (95% confidence interval 0.3 to 0.8, col. 5).

We next examine how time spent cooking (as measured by Stove Usage Monitors) predicts kilograms of wood use (Table 6). In the pooled regression, 10 hours of additional cooking (about one standard deviation, and about two thirds of the mean) predicted 1.24 kilograms higher wood use (95% confidence interval 6.8 to 18, col. 1). This point estimate is about a fourth of a standard deviation and about 13% of the mean of wood use. The modest R^2 (9.8%) is consistent with measurement error in wood use, measurement error in time cooking, and with stoves varying substantially in wood consumption per hour cooking.

When we include fixed effects for each household (col. 2), the estimate implies that on days a household cooked 10 hours longer than normal, it used 1.4 kilograms more wood (95% CI = -0.2 to 3.2). This point estimate is about one third larger than that in the pooled analysis, but the increase is not statistically significant.

Hours spent cooking on the primary three-stone fire (as identified by the household) has a stronger relationship with wood use (β = 0.19, 95% CI = 0.06 to 0.32, column 3) than hours on the secondary three-stone fire (β = 0.05, 95% CI = -0.08 to 0.18, column 3). We are not sure why the secondary stove point estimate is so close to zero. These results are consistent with a larger fire on the primary stove, and the secondary stove often being used for reheating a sauce or making a separate meal for a child or person on restricted diet. There is no large or statistically significant effect of squared minutes on either stove (col. 5 and 6).

We next examine how well the number of lunch or dinner meals cooked (based on self-reported data) predicts particulate matter (PM) concentrations, as measured by UCB-PATS (Table 7). Cooking dinner or lunch had no statistically significant effect on daily average particulate matter concentration. The instances of beans or matooke cooked also had no statistically significant effect on daily average particulate matter concentration. Cooking for one additional person (looking at the maximum of lunch and dinner) predicts 80-$\mu g/m^3$ higher average PM concentration (about 8% of the standard deviation and also of the mean, 95% confidence interval 18 to 144 $\mu g/m^3$, col. 5).

We review how well time spent cooking (as measured by stove usage monitors) predicts particulate matter (PM) concentration (as measured by UCB-PATS, Table 8). Pooling across homes, there is no large or statistically significant effect of time spent cooking on average PM concentration (β = 1.7, 95% CI = -12.8 to 16.1, col. 1). When we include a fixed effect for each household (col. 2), the estimate implies that on days a household cooked 10 hours longer than normal (about one standard deviation), PM concentrations increased by 306 $\mu g/m^3$ (about a fourth of a standard deviation, 95% CI = 79 to 532).

If we examine how well time spent cooking predicts primary stove usage (as identified by the household) versus the secondary stove and include a fixed effect for each household, hours cooking on the primary stove (β = 42, 95% CI = 2 to 81, column 4) has a stronger relationship with PM concentration than hours on the secondary stove (β = 19, 95% CI = -

22 to 60, column 4). These results are consistent with a larger fire on the primary stove. There is no large or statistically significant effect of squared minutes on either stove (col. 5 and 6).

We last examine how well kilograms of wood use predict particulate matter (PM) concentrations, as measured by UCB-PATS (Table 9). In the pooled regression, one additional kilogram of wood used (15% of the standard deviation, and 11% of the mean) predicted a 46-$\mu g/m^3$ increase in PM concentration (about 5% of a standard deviation, 95% CI = 12 to 79). Although the coefficient is sizable, the R^2 is only 4.3%.

When we include a fixed effect for each household (col. 2), the estimate implies that on days a household used one additional kilogram of wood, PM concentrations increased by 30 $\mu g/m^3$ (95% CI = 5 to 54). The decline relative to the result in col. 1 is not statistically significant.

4. Conclusions and Policy Implications

We find statistically significant positive correlations between almost all pairs of our various proxies for cooking: estimated time spent cooking (based on a predictive logistic regression using stove use monitor (SUM) temperature readings and visual observations), number of people cooked for gathered from food diaries, kilograms of wood used, and particulate matter (PM) concentrations. While the correlations are positive, the explanatory power of each regression is low. In addition, we find no statistically significant correlation between

PM concentrations and our estimated time spent cooking. Within-household estimators eliminate the bias of time-invariant omitted variables (e.g., ventilation, altitude, etc.). However, when we controlled for these household fixed effects, estimates were imprecise because most households did not change their cooking very much from day to day.

Some variation in outcomes is due to our measures being conceptually distinct: Wood use is not the same as particulate matter concentration or hours of cooking. Additional variation in outcomes is due to variation in homes (e.g., ventilation), fuel (wet or dry), stoves (good or bad airflow), and so forth. At the same time, the very modest R^2 values we estimate are consistent with substantial measurement error in most or all of our measures. We cannot determine if the measurement error is largely due to low reliability (random error) or low validity (bias).

These findings may be useful for other projects in determining what methods to use to analyze cooking events. Specifically, our findings emphasize the importance of multiple measures to understand cooking practices and how new stoves change those practices. These findings are suggestive of the difficulties of auditing carbon credits for fuel-efficient cookstoves. To the extent measures of fuel (and carbon) savings use only a single metric such as a kitchen performance test and use only a modest sample size, results can have substantial measurement error. For carbon credits to have the desired public effect of lowering carbon emissions and the desired private effect of improving household health it will be important to continue advancing stove usage monitors and other stove measurement techniques.

Acknowledgments

This study was funded by the United States Agency for International Development under Translating Research into Action, Cooperative Agreement No. GHS-A-00-09-00015-00. The recipient of the grant was Impact Carbon who co-funded and managed the project. We thank Impact Carbon partners Matt Evans, Evan Haigler, Jimmy Tran, Caitlyn Toombs, and Johanna Young; Berkeley Air project partners including Dana Charron, Dr. David Pennise, Dr. Michael Johnson, and Erin Milner; and the USAID TRAction Technical Advisory Group. Special thanks to Kirk Smith, Ilse Ruiz-Mercado, Ajay Pillarisetti and colleagues from the U.C. Berkeley Household Energy, Climate, and Health Research Group for the development of the Stove Use Monitoring system concept and consultations on optimal placement and holder design for this project. Data collection was carried out by the Center for Integrated Research and Community Development (CIRCODU), and the project's success relied on expert oversight by CIRCODU's Director General Joseph Ndemere Arineitwe, primary supervisor Juliet Kyayesimira and other field supervisors Moreen Akankunda, Innocent Byaruhanga, Fred Isabirye, Noah Kirabo, and Michael Mukembo. This study was made possible by the support of the American people through the United States Agency for International Development (USAID). The findings of this study are the sole responsibility of the authors, and do not necessarily reflect the views of their respective institutions, nor USAID or the United States Government.

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Table 1: Daily hours cooked, particulate matter concentrations, and food diary data

Variable	Mean	Std. Dev.	Min.	Max.	N
Hours main stove cooked adjusted by reliability	8.18	7.02	0	31.04	219
Hours secondary stove cooked adjusted by reliability	5.85	6.22	0	25.06	219
Hours main and secondary stove cooked combined adjusted by reliability	14.04	10.24	0.3	49.44	219
Hours main stove cooked adjusted by reliability and centered and squared	49.04	52.3	0	522.24	219
Hours secondary stove cooked adjusted by reliability and centered and squared	38.52	50	0	368.92	219
Average Particulate Matter concentration (micrograms/m3)	1018.94	1001.13	7.19	5548.01	366
Number of meals cooked per day	3.34	0.89	0	4	391
Cooked lunch (1), dinner (1), or both (2)	1.85	0.4	0	2	400
Number of instances of beans or matooke per day	2.48	1.04	0	4	400
Net wood used daily (weight in kg)	9.9	6.56	0	47.5	359
Net wood used daily with top 5% coding (weight in kg)	9.09	4.52	0	17	359
Total number of people that breakfast was cooked for	5.37	3	0	14	403
Total number of people that lunch was cooked for	5.28	2.84	0	16	403
Total number of people that tea was cooked for	4.36	3.44	0	15	403
Total number of people that dinner was cooked for	6.09	2.38	0	12	403
Max number of people cooked for lunch or dinner	6.34	2.36	0	16	403

Source: Baseline data. The unit of analysis is the time between two sequential visits comprising approximately a 24 hour period. In a small number of cases the time between two visits was 48 hours.

Notes: Hours cooked is derived from a predictive logistic regression of temperature data on observations of stoves in use. The process is described in detail in Simons et al. (2014).

Average Particulate Matter concentration is based on protocol for UCB Particle And Temperature Sensors (UCB PATS) produced by Berkeley Air Monitoring Group.

Net wood used is calculated after dropping 17 observations of negative wood weights, which likely occurred when households added wood to the designated pile before it was weighed.

Max number of people cooked for lunch or dinner takes the highest value of either lunch or dinner as those meals are the bulk of cooking.

Table 2: Common lunch and dinner foods

Variable	Mean	Std. Dev.	N
Matooke for lunch	0.78	0.41	401
Matooke for dinner	0.71	0.45	402
Matooke for lunch and dinner	0.57	0.49	400
Beans for lunch	0.42	0.49	401
Beans for dinner	0.56	0.5	402
Beans for lunch and dinner	0.28	0.45	400
Number of instances of beans or matooke per day	2.48	1.04	400
Proportion of days households cooked lunch	0.89	0.31	401
Proportion of days households cooked dinner	0.96	0.2	402

Note: All variables (except "No. of instances of matooke or beans") are dummy variables.

Table 3: Minutes cooked on three stone fire (TSF)

Variable	Mean	Std. Dev.	N
Daily hours above 34C for TSF 1st	12	10.1	219
Daily hours above 34C for TSF 2nd	8.7	9.2	219
Daily hours above 36C for TSF 1st	10.2	9.6	219
Daily hours above 36C for TSF 2nd	7	8.4	219
Daily hours above 38C for TSF 1st	8.5	8.8	219
Daily hours above 38C for TSF 2nd	5.6	7.8	219
Daily hours above 40C for TSF 1st	6.9	7.9	219
Daily hours above 40C for TSF 2nd	4.5	6.9	219
Daily hours above 42C for TSF 1st	5.6	7.3	219
Daily hours above 42C for TSF 2nd	3.6	6.2	219

Note: TSF 1st refers to the main cookstove and TSF 2nd refers to the secondary cookstove.

Table 4: Number of hours spent cooking and food diaries

Dependent variable = No. of hours cooked daily adjusted by reliability

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Cooked lunch (1), dinner (1), or both (2)	5.536***	1.995**	4.317**	1.563	4.360**	1.553
	(1.383)	(0.957)	(1.711)	(1.042)	(1.744)	(1.047)
Number of instances of beans or matooke per day			0.925	0.409	0.494	0.393
			(0.793)	(0.391)	(0.795)	(0.398)
Max number of people cooked for lunch or dinner					0.722**	0.0537
					(0.309)	(0.224)
Constant	3.952*		3.913*		0.364	
	(2.308)		(2.344)		(2.959)	
Observations	215	215	215	215	215	215
R-squared	0.043	0.034	0.049	0.042	0.076	0.043
Hausman Test (Prob>chi^2)		0.110		0.298		0.277
Number of household fixed effects		90		90		90

Robust standard errors adjusted for clustering by household in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects), or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

Table 5: Daily wood used for cooking and food diaries
Dependent variable = kg. of wood used daily

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Cooked lunch (1), dinner (1), or both (2)	1.754**	0.993	1.758**	0.984	1.737**	1.011
	(0.729)	(0.663)	(0.777)	(0.747)	(0.754)	(0.752)
Number of instances of beans or matooke per day			-0.00257	0.00787	-0.240	0.0247
			(0.280)	(0.297)	(0.266)	(0.300)
Max number of people cooked for lunch or dinner					0.542***	-0.0778
					(0.113)	(0.186)
Constant	5.854***		5.854***		3.029**	
	(1.406)		(1.407)		(1.468)	
Observations	357	357	357	357	357	357
R-squared	0.022	0.011	0.022	0.011	0.096	0.012
Hausman Test (Prob>chi^2)		0.280		0.548		0.011
Number of household fixed effects		152		152		152

Robust standard errors adjusted for clustering by household in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects), or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

Table 6: Daily wood used for cooking and number of hours spent cooking
Dependent variable = kg. of wood used daily

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Hours main stove cooked adj. by reliab.			0.191***	0.0307	0.166**	0.0570
			(0.0637)	(0.150)	(0.0659)	(0.182)
Hours main stove cooked adj. by reliab., cntrd. and sq.					0.00572	-0.00400
					(0.00983)	(0.0162)
Hours secondary stove cooked adj. by reliab.			0.0456	0.268*	0.00678	0.221
			(0.0656)	(0.159)	(0.0867)	(0.211)
Hours secondary stove cooked adj. by reliab., cntrd. and sq.					0.00697	0.00688
					(0.00834)	(0.0211)
Hours main and secondary stove cooked adj. by reliab.	0.124***	0.144				
	(0.0284)	(0.0872)				
Constant	6.487***		6.409***		6.286***	
	(0.517)		(0.529)		(0.596)	
Observations	196	196	196	196	196	196
R-squared	0.098	0.024	0.118	0.032	0.127	0.033
Hausman Test (Prob>chi^2)		0.821		0.349		0.699
Number of households fixed effects		85		85		85

Robust standard errors adjusted for clustering by household in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects, or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

Table 7: Daily Particulate Matter concentrations and food diaries
Dependent variable = PM concentrations in micrograms per meter cubed

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Cooked lunch (1), dinner (1), or both (2)	160.9	30.04	150.7	90.13	128.3	76.58
	(125.9)	(110.8)	(168.7)	(125.1)	(159.0)	(124.3)
Number of instances of beans or matooke per day			7.449	-51.37	-26.72	-67.10
			(66.26)	(49.64)	(64.49)	(49.80)
Max number of people cooked for lunch or dinner					79.72**	62.02**
					(32.34)	(29.29)
Constant	726.5***		726.8***		352.1*	
	(237.1)		(237.9)		(201.3)	
Observations	362	362	362	362	362	362
R-squared	0.004	0.000	0.004	0.005	0.039	0.026
Hausman Test (Prob>chi^2)		0.259		0.467		0.733
Number of household fixed effects		148		148		148

Robust standard errors adjusted for clustering by household in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects), or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

Table 8: Daily Particulate Matter concentrations and number of hours spent cooking
Dependent variable = PM concentrations in micrograms per meter cubed

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Hours main stove cooked adj. by reliab.			-17.15	41.51**	-18.97	49.45**
			(13.32)	(19.91)	(15.52)	(22.77)
Hours main stove cooked adj. by reliab., cntrd. and sq.					0.691	-1.668
					(1.333)	(2.279)
Hours secondary stove cooked adj. by reliab.			24.21	19.05	24.10	18.17
			(16.89)	(20.64)	(21.65)	(23.69)
Hours secondary stove cooked adj. by reliab., cntrd. and sq.					0.0661	0.119
					(2.170)	(2.945)
Hours main and secondary stove cooked adj. by reliab.	1.691	30.58***				
	(7.266)	(11.44)				
Constant	871.8***		884.7***		864.7***	
	(144.1)		(145.9)		(134.6)	
Observations	204	204	204	204	204	204
R-squared	0.000	0.057	0.036	0.060	0.038	0.065
Hausman Test (Prob>chi^2)		0.027		0.031		0.113
Number of Household fixed effects		84		84		84

Robust standard errors adjusted for clustering by household in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects), or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

Table 9: Daily Particulate Matter concentrations and wood used for cooking
Dependent variable = PM concentrations in micrograms per meter cubed

	(1)	(2)
VARIABLES	OLS	FE
Net wood used daily with top 5% coding (weight in kg)	45.52***	29.82**
	(17.17)	(12.47)
Constant	614.2***	
	(150.4)	
Observations	329	329
R-squared	0.043	0.030
Hausman Test (Prob>chi^2)		0.726
Number of household fixed effects		142

Robust standard errors adjusted for clustering by household in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The Hausman test examines whether we can reject that the random effects estimator is consistent (in which case it will be more efficient than fixed effects), or whether we should only rely on the fixed effects estimator. For definitions of variables see Table 1 footnotes.

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