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What is a “Meal”? Comparing Methods to Determine Cooking Events

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What is a “Meal”? Comparing Methods to Determine Cooking Events

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Abstract

There are numerous methods to measure cookstove use. This paper compares data from Stove Usage Monitors (SUMs) that log temperature of stoves (which we convert to estimated time spent cooking), physical observations of cooking by enumerators, food diaries (that record meals cooked, stoves used, and number of people cooked for), kitchen performance tests (KPTs) that weigh fuels before and after cooking, and particulate matter (PM) monitors. These data were collected as part of a larger study in rural western Uganda. Supporting the validity of each measurement, we find statistically significant positive correlations between each pair of

- estimated time spent cooking;

- number of people cooked for;
- kilograms of wood used; and
- particulate matter concentrations

While the correlations are all positive, the explanatory power of the regressions is always low. These results suggest the measures have some validity, but validity is modest. Our findings emphasize the importance of multiple measures.

Introduction

Half the world cooks on inefficient stoves that burn solid fuels such as wood and charcoal. Inefficient cookstoves harm child and maternal health and contribute to deforestation and global climate change. Household air pollution accounts for an estimated 4 million deaths a year- 3.5 due to direct exposure and 0.5 million deaths from outdoor air pollution from cook fires (Lim et al., 2012).

Improved cookstove technologies can reduce household air pollution and its resulting harm to health (Bruce et al., 2007; Ezzati & Kammen, 2002; McCracken et al., 2007; Smith et al., 2010; Smith-Sivertsen et al., 2009). Furthermore, where fuel regrows more slowly than it is harvested, improved stoves could reduce deforestation (Arnold, Köhlin, & Persson, 2006; Wooten, 2003). Given the vast numbers of households across the globe that use traditional stove technologies, mass adoption of efficient stoves has the potential for substantial reductions in greenhouse gas emissions. Additionally, both the health burden of household air pollution and the time burden collecting biomass for fuel is concentrated on women and children (Kammen, Bailis, & Herzog, 2002). Finally, in some areas women and girls are made vulnerable to sexual violence as they often must travel alone and far from their homes in search of firewood (Patrick, 2007).

To understand the effects of new stoves, it is not enough to measure their ownership. It is crucial to measure both use of the new stove *and* any reduction in use of traditional stoves (Miller & Mobarak, 2011; Ruiz-Mercado, Masera, Zamora, & Smith, 2011). For example, many owners of new stoves continue to use old stoves and fuels. Such stove “stacking” can ensure reductions in fuel use and household air pollution are minimal.

Stove designers, manufacturers, and marketers need to know how consumers use stoves and how new stoves do or do not fit consumers’ needs. The carbon market needs to know if new stoves deserve credits for lower emissions¹. For example, how well do stove usage measures during an intense period of measurement match periods when there are not daily visits from a stove monitoring team? All these questions depend on knowing how much people use old and new stoves.

This paper focuses on understanding how to determine stove use. This paper compares five different measurements: Stove Usage Monitors (SUMs) that log temperature of stoves; physical observations of cooking; food diaries that record meals cooked, stoves used, and number of

people cooked for; kitchen performance tests (KPTs) that measure weights of fuels used before and after cooking; and Particulate Matter (PM) monitors that measure PM concentrations in air. This paper aims to compare these five techniques in order to determine the validity and utility of each method. This study will add to the literature by helping future researchers decide which technique or combination of techniques is most useful to understand stove usage. This study will help determine the validity of each technique by comparing results from the five techniques with each other. By doing so, this study will assist stove designers, distributors, and development professionals in assessing the long-term impact of introduction of clean cooking technologies.

Literature Review

Measuring stove usage

Some studies have used stove usage monitors (SUMs) to record temperatures of stoves to determine (Ruiz-Mercado, Canuz, Walker, & Smith, 2013; Ruiz-Mercado, Lam, Canuz, Davila, & Smith, 2008). SUMs readings can be difficult to interpret because readings vary based on distance from the heat source. For traditional cooking methods it is particularly difficult to have consistent distances from the heat source. Also, SUMs become damaged when exposed to high temperatures. This damage is particularly problematic if damaged SUMs are non-random; for example, at homes that cook more than average.

Physical observations are another uncommon measurement for improved cookstove studies. They have been used to verify fuel supply, stove use, and food preparation (Wallmo, 1996).

Although not a common measurement used in improved cookstove studies, food diaries have been used in other studies as a useful tool to understand populations' diets (Krall & Dwyer, 1987; Prentice, 2003). Food diaries can be inaccurate because of recall bias and experimenter demand effects (if respondents over-report use of stoves that the experimenter is interested in). Food diaries also do not directly measure the duration of cooking (although they can include proxies such as what dishes were cooked).

The Kitchen Performance Test (KPT) is the principal field-based procedure to demonstrate the effect of stove interventions on household fuel consumptionⁱⁱ. The KPT includes measuring wood available for cooking over the next 24 hours and then returning a day later and measuring the remaining wood. Leading researchers advise the KPT testing period should be for 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. The final fuel weighed may include additional wood that was not in the original pile. Alternatively, the family may have used some wood in the original pile for a purpose other than their cooking (e.g., to lend to a neighbor). Wood also may get wet between the initial and final weighing.

Particulate Matter (PM) monitors have been used to measure concentrations of particles in wood smoke from cooking that have negative health effects (McCracken et al., 2007; Smith et al., 2010). PM monitor data is difficult to interpret as they are not standardized and the relationship of cooking to PM concentrations depends on stove type and fuel, type of cooking (high or low temperature, smoldering wood, etc.), airflow in the kitchen, and other factors.

Water boiling tests (WBTs) and controlled cooking test (CCTs) have been used in cookstove studies. These tests have proven to be more useful for measuring stove efficiency in the laboratory rather than measuring stove usage by households in the field (Smith et al., 2007).

Comparing measures of stove usage

Few studies compare different methods for measuring usage. Most of the studies done in the past have used one or two methods to determine stove usage. In Smith et al. (2010), PM concentrations were compared with CO concentrations, but there was no comparison with weights of wood used or time spent cooking. In Ruiz-Mercado et al. (2013), time spent cooking (using SUMs) was compared with food diaries that used recall questionnaires and results were found to be consistent. Our study aims to compare five methods to understand validity of each method.

Overview of Cooking Practices in our Study Zone

This study took place in rural parts of the Mbarara district, in the Western region of Uganda. The main economic activity is agrarian including farming of *matooke*, 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 window.

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* (unripe plantains) 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.

Methods

This study took place from March through September of 2012. The Mbarara region was chosen because it is rural, almost all families cooked on a traditional three-stone fire, there was no active improved cookstove interventions, it was less than a day's travel from Kampala, and families spent a lot of time gathering wood (see Web Appendix 2, Figure 2C).ⁱⁱⁱ The Centre for Integrated Research and Community Development (CIRCODU), an NGO that specializes in evaluation of clean cookstoves, distributed stoves and collected data for the project.

Almost all families in rural Mbarara cook on a traditional three-stone fire (TSF), usually located within a cooking hut (see Web Appendix 2, Figure 2C). 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 is the focus of a subsequent study.

We held 14 parish-level sales meetings where we offered the Envirofit stove. (A parish is a handful of villages.) 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 cooks for eight or fewer (the Envirofit is able to cook Ugandan-size portions for at most eight people), someone is home every day, and cooking is 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.

In this paper we analyze data from the baseline measurements. 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 the temperatures on each stove in the household 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 cooked for each meal; the amount of fuel used via Kitchen Performance Tests (KPTs); and particulate matter concentrations using University of California, Berkeley Particle and Temperature Sensors (UCB-PATS).

The Stove Usage Monitor (SUM) is a micro-chip enclosed in a 16mm thick stainless steel case, which we 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.^{iv} The vast majority of households (97%) use two three-stone fires to cook 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.

Each SUM was placed in a SUM holder, which is a metallic shell used to prevent overheating of the ibuttons (which cannot survive temperatures over 85°C). We then placed the SUM,

enclosed in the SUM holder, underneath one of the stones of each of the two three-stone fires. Approximately every four weeks we collected the SUMs and replaced them with new SUMs.

The individual SUMs readings were coupled with the ‘rapid observations’ (when a stove was physically observed as on or off) to create a logistic regression that predicts the probability that a given stove is in use based on the temperature readings from the SUMs devices.

Physical observations of stoves in use, or rapid observations, were recorded by the data collection team 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. We originally intended to use the entire rapid observations sample directly. We found, however, a number of anomalies. For example, 3.0% (10 out of 329) rapid observations report a three-stone fire was “lit” and had SUM readings below the typical daily mean temperature (23.8°C) in this setting. Another 7.8% (105 out of 1339 rapid observations) had rapid observations of “not lit” when the SUM reading was over 40°C, which was the highest ambient air temperature recorded in the observation period. While we would have preferred to use all of these rapid observations, we suspect that a substantial share of these cases are due to errors in observing or recording the lit status of stoves, or errors in matching the timestamps, household, or stoves with the rapid observation. Given normal diurnal ambient temperature patterns (cooler at night, warmest in the afternoon), we adjust rapid observations by removing rapid observations observed as “lit” but with temperatures lower than 2.0°C less than the mean ambient temperature of the hour of the rapid observation. We also removed rapid observations observed as “not lit” if they were more than 2.0°C above the maximum ambient temperature for that hour.

Coupling the SUMs temperature readings with the adjusted rapid observations of visual stove usage allows for a logistic regression to predict stove usage across the entire sample. Using the following specification:

$$RO_{it} = F(T_{it} + T_{it-1} + T_{it+1} + T_{it-2} + T_{it+2} + e_{it}) \quad (1)$$

where $F(.)$ is the logistic functional form, RO_{it} is a dummy variable for adjusted rapid observations for stove i at time t . T_{it} is the SUMs temperature reading for stove i at time t . T_{it-1} is the SUMs temperature reading for stove i at time $t-1$. $T_{it+\tau}$ is the SUMs temperature reading for stove i at time $t+\tau$, for $\tau = -2, -1, 1, \text{ and } 2$ (that is 30 and 60 minutes prior to the rapid observation, and 30 and 60 minutes after) and e_{it} is an error.

Specifying the logistic regression in this way gives a pseudo R-squared of 0.40 and correctly classifies 88% of the three stone fire rapid observation sample. Based on the results of the logistic regression we predict the probability of cooking throughout the entire sample. The probability of cooking is multiplied by the number of minutes elapsed between two temperature readings to create the predicted minutes cooked. We use predicted minutes cooked to determine the number of hours per day the household uses each three-stone fire.

Enumerators collected a food diary at the end of each 24-hour measurement period. Households listed the foods cooked, fuels used and number of people cooked for each meal in the last 24 hours. In addition, households reported any special event in the last 24 hours (for example, a large party).

The Kitchen Performance Test (KPT) measures the amount of fuel used over a 24 hour period by setting aside fuel to be used for the next 24 hours, weighing the initial amount of fuel, and then returning 24 hours later to weigh the remaining amount of fuel. Over 99% of the fuel was wood. We measured three consecutive days, avoiding weekends and holidays (Bailis et al., 2007). The KPT required four household visits, from Tuesday to Friday. 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. As all households used wood, the cook was asked to separate a pile of wood that they estimated would be used in the next 24 hours. 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. A similar procedure was used for households that anticipate cooking with charcoal. Then the anticipated fuel to be used was weighed. The wood and/or charcoal were then placed in a separate pile and households were instructed to only use fuel from the weighed piles. In 24^v hours, the data collection team returned and weighed the remaining fuel.

The UCB-PATS uses light scattering to measure particular matter of less than 2.5 microns (PM_{2.5}). We placed UCB-PATS in study participants' homes for 72 hours. At the start of the study we calibrated all UCB PATS using a "gold standard" pump and filter laboratory chamber calibration. In addition, at the end of the study we calibrated all UCB-PATS with a reference UCB-PATS that was never used in the field. Laboratory calibrations produced a particle coefficient ratio which adjusts the factory calibrated PC ratio to account for the aerosol-specific size distribution of particles found in the main study. The resulting PC Ratio is used to convert UCB-PATS readings from Δmv to $\mu g/m^3$.

Statistical methods

We compared each of the cooking event measurements by using pooled and within household regressions. Pooled regressions included clustering by household. Within household estimators reduce omitted variables that are constant in a household (e.g., ventilation), but little variation remains on some measures.

Results

Descriptive Statistics

Stove Use Monitors

Table 1 shows 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.

Food Diaries

In total there are 1,306 meals cooked in 391 days measured, averaging 3.34 meals per day (Table 1). Most stove usage occurs during lunch and dinner preparation; 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 of people cooked for lunch and/or dinner reported by households had an average of 6.34 people (Table 1).

Wood Weights from Kitchen Performance Tests

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

Particulate Matter Concentrations

There are 366 days of Particulate Matter concentrations measurements with an average PM concentration of 1019 $\mu\text{g}/\text{m}^3$. For comparison, the U.S. standard for outdoor air pollution is 35^{vii} $\mu\text{g}/\text{m}^3$.

Regression Analyses

We first examine how well the number of lunch or dinner meals cooked (based on self-reported data) predicts time spent cooking, as measured by our Stove Usage Monitors (Table 4). In the pooled regression households cooking lunch or dinner predicts 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 4.0%.

When we include a fixed effect for each household (col. 2), the estimate implies that on days a household cooked lunch or dinner (exclusively), the household cooked 2.1 hours longer than normal (95% CI = 0.2 to 4.1).

When we include instances of cooking beans or matooke for lunch or dinner, 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 1.4, col. 5).

We next examine how well the number of lunch or dinner meals cooked (based on self-reported 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 instances of cooking beans or matooke for lunch or dinner, 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 well time spent cooking (as measured by our 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 1.20 kilograms higher wood use (95% confidence interval 6.1 to 17, 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 (9.2%) 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 a fixed effect for each household (col. 2), the estimate implies that on days a household cooked 10 hours longer than normal, it used 1.6 kilograms more wood (95% CI = 0.00 to 3.0). 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 stove (as identified by the household) has a stronger relationship with wood use ($\beta = 0.19$, 95% CI = 0.06 to 0.31, column 3) than hours on the secondary stove ($\beta = 0.038$, 95% CI = -0.085 to 0.16, 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 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 $\mu\text{g}/\text{m}^3$ higher average PM concentration (95% confidence interval 18 to 144, col. 5).

We next examine 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 ($\beta = 1.8$, 95% CI = -12.3 to 15.9, 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 289 $\mu\text{g}/\text{m}^3$ (about a fourth of a standard deviation, 95% CI = 70 to 509).

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 ($\beta = 39$, 95% CI = -1 to 80, column 4) has a stronger relationship with PM concentration than hours on the secondary stove ($\beta = 18$, 95% CI = -23 to 59, 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 $46 \mu\text{g}/\text{m}^3$ 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 $30 \mu\text{g}/\text{m}^3$ (95% CI = 5 to 54). The decline relative to the result in col. 1 is not statistically significant.

Conclusion

Summary

Supporting the validity of each measurement, we find statistically significant positive correlations between each pair of

- estimated time spent cooking;
- number of people cooked for;
- kilograms of wood used; and
- particulate matter concentrations

In addition to these findings, we find no statistically significant correlation between the following:

- time spent cooking and instances of cooking beans or matooke
- Weight of wood used and instances of cooking beans or matooke
- PM concentrations and instances of cooking beans or matooke
- PM concentrations and cooking lunch or dinner
- PM concentrations and time spent cooking

We find no instances of statistically significant correlations that go against our hypotheses. Thus, these results suggest that each measure has some validity, but validity is modest. Our findings emphasize the importance of multiple measures in order to get an accurate picture of cooking events.

Discussion

It is surprising to find statistically significant positive correlations between cooking lunch or dinner and time spent cooking/wood used, but no statistically significant correlation between cooking lunch or dinner and PM concentrations. It is also surprising to find statistically significant positive correlations between wood used and time spent cooking/PM concentrations, but no statistically significant correlation between PM concentrations and time spent cooking. These results suggest that there is significant measurement error among the various methods. Some 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 many of our measures. Some error is due to household differences, but unfortunately within estimates (that wipe out household omitted characteristics) have low power (not much variation).

These findings may be useful for other projects. Given the strong measurement error associated with measuring time spent cooking on traditional cookstoves, it may be wiser to rely on wood usage to serve as a proxy for time spent cooking.

Next steps

Should we talk about next steps with data analysis of stove usage after the introduction of the Envirofit? Should we talk about what future studies need to be done to further understand stove usage?

Bibliography

- Arnold, J. E. M., Köhlin, G., & Persson, R. (2006). Woodfuels, Livelihoods, and Policy Interventions: Changing Perspectives. *World Development*, 34(3), 596–611. doi:10.1016/j.worlddev.2005.08.008
- Bruce, N., Weber, M., Arana, B., Diaz, A., Jenny, A., Thompson, L., ... Smith, K. R. (2007). Pneumonia case-finding in the RESPIRE Guatemala indoor air pollution trial: standardizing methods for resource-poor settings. *Bulletin of the World Health Organization*, 85(7), 535–544. doi:10.2471/BLT.06.035832
- Ezzati, M., & Kammen, D. M. (2002). Evaluating the health benefits of transitions in household energy technologies in Kenya. *Energy Policy*, 30(10), 815–826. doi:10.1016/S0301-4215(01)00125-2
- Kammen, D. M., Bailis, R., & Herzog, A. (2002). *Clean Energy for Development and Economic Growth: Biomass and Other Renewable Energy Options to Meet Energy and Development Needs in Poor Nations* (pp. 1–121). New York: UNDP and Government of Morocco.
- Krall, E. A., & Dwyer, J. T. (1987). Validity of a food frequency questionnaire and a food diary in a short-term recall situation. *Journal of the American Dietetic Association*, 87(10), 1374–7. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/3655166>
- Lim, S. S., Vos, T., Flaxman, A. D., Danaei, G., Shibuya, K., Adair-Rohani, H., ... Aryee, M. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010. *Lancet*, 380(9859), 2224–60. Retrieved from <http://www.ncbi.nlm.nih.gov/pubmed/23245609>
- McCracken, J., Schwartz, J., Mittleman, M., Ryan, L., Artiga, A. D., & Smith, K. R. (2007). Biomass Smoke Exposure and Acute Lower Respiratory Infections Among Guatemalan Children. *Epidemiology*, 18(5), S185.
- Miller, G., & Mobarak, A. M. (2011). INTRA-HOUSEHOLD EXTERNALITIES AND LOW DEMAND FOR A NEW TECHNOLOGY: EXPERIMENTAL EVIDENCE ON IMPROVED COOKSTOVES. *unpublished*.
- Patrick, E. (2007). Sexual violence and firewood collection in Darfur. *Forced Migration Review*, 27, 40–41.
- Prentice, R. L. (2003). Dietary assessment and the reliability of nutritional epidemiology reports. *Lancet*, 362(9379), 182–3. Retrieved from <http://www.thelancet.com/journals/a/article/PIIS0140-6736%2803%2913950-5/fulltext>

- Ruiz-Mercado, I., Canuz, E., Walker, J. L., & Smith, K. R. (2013). Quantitative metrics of stove adoption using Stove Use Monitors (SUMs). *Biomass and Bioenergy*, null(null). Retrieved from <http://dx.doi.org/10.1016/j.biombioe.2013.07.002>
- Ruiz-Mercado, I., Lam, N. L., Canuz, E., Davila, G., & Smith, K. R. (2008). Low-cost temperature loggers as stove use monitors (SUMs). *Boiling Point*, 55, 16–18.
- Ruiz-Mercado, I., Masera, O., Zamora, H., & Smith, K. R. (2011). Adoption and sustained use of improved cookstoves. *Energy Policy*, 39(12), 7557–7566. doi:10.1016/j.enpol.2011.03.028
- Smith, K. R., Dutta, K., Chengappa, C., Gusain, P. P. S., Masera, O., Berrueta, V., ... Shields, K. N. (2007). Monitoring and evaluation of improved biomass cookstove programs for indoor air quality and stove performance : conclusions from the Household Energy and Health Project. *Energy for Sustainable Development*, XI(2), 5–18.
- Smith, K. R., McCracken, J. P., Thompson, L., Edwards, R., Shields, K. N., Canuz, E., & Bruce, N. (2010). Personal child and mother carbon monoxide exposures and kitchen levels: methods and results from a randomized trial of woodfired chimney cookstoves in Guatemala (RESPIRE). *Journal of Exposure Science and Environmental Epidemiology*, 20(5), 406–16. doi:10.1038/jes.2009.30
- Smith-Sivertsen, T., Díaz, E., Pope, D., Lie, R. T., Díaz, A., McCracken, J., ... Bruce, N. (2009). Effect of reducing indoor air pollution on women’s respiratory symptoms and lung function: the RESPIRE Randomized Trial, Guatemala. *American Journal of Epidemiology*, 170(2), 211–20. doi:10.1093/aje/kwp100
- Wallmo, K. (1996). Improved cookstoves in Western Uganda. Retrieved from <http://ufdc.ufl.edu/UF00056227/00001>
- Wooten, S. (2003). Losing ground: gender relations, commercial horticulture, and threats to local plant diversity in rural Mali. In P. Howard (Ed.), *Women and plants: gender relations in biodiversity management and conservation* (pp. 229–242). London: ZED Books.

ⁱ For more details, see <http://www.cdmgoldstandard.org/frequently-asked-questions/carbon-market>.

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

ⁱⁱⁱ 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.

^{iv} 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.

^v The team attempted to return to households in exactly 24 hours, but exact time varied with 96% of visits between 20.4 and 27.6 hours of the previous visit.

^{vi} There are actually 376 measures of wood weights, but 17 are negative values (4.5% of the data), which have been dropped from 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.

^{vii} See <http://www.epa.gov/air/criteria.html> for details.

Table 1: Hours Cooked, PM Concentrations, and Food Diary Data

Variable	Mean	Std. Dev.	Min.	Max.	N
Hours main stove cooked	8.98	7.21	0	37.79	219
Hours secondary stove cooked	6.67	6.38	0	25.69	219
Hours main and secondary stove cooked combined	15.65	10.49	0.11	58.16	219
Hours cooked on main stove centered and squared	53.8	82.12	0	915.66	219
Hours cooked on secondary stove centered and squared	42.65	67.74	0	420.3	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
No. of instances of beans or matooke	2.48	1.04	0	4	400
Net wood used (weight in kg)	9.9	6.56	0	47.5	359
Net wood used with top 5% coding (weight in kg)	9.09	4.52	0	17	359
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 logit based on SUMs temperature readings and rapid observations of stoves in use after removing the cases of rapid observations that were "on" and less than 23.8C and "off" but higher than 40C. Only households with SUMs on every cookstove is included in this logit.

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
No. of instances of beans or matooke	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

Table 3: Minutes Cooked

Variable	Mean	Std. Dev.	N
Daily total minutes above 34C between KPT visits for TSF 1st	719.8	605.1	219
Daily total minutes above 34C between KPT visits for TSF 2nd	522.4	553.2	219
Daily total minutes above 36C between KPT visits for TSF 1st	611.7	573.7	219
Daily total minutes above 36C between KPT visits for TSF 2nd	417.8	505.7	219
Daily total minutes above 38C between KPT visits for TSF 1st	508.8	530.2	219
Daily total minutes above 38C between KPT visits for TSF 2nd	336.1	465.1	219
Daily total minutes above 40C between KPT visits for TSF 1st	414.2	476.8	219
Daily total minutes above 40C between KPT visits for TSF 2nd	270.6	414.1	219
Daily total minutes above 42C between KPT visits for TSF 1st	338.5	438.8	219
Daily total minutes above 42C between KPT visits for TSF 2nd	218.9	371.4	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

VARIABLES	(1) OLS	(2) FE	(3) OLS	(4) FE	(5) OLS	(6) FE
Cooked lunch (1), dinner (1), or both (2)	5.527*** (1.382)	2.131** (0.994)	4.150** (1.729)	1.646 (1.082)	4.192** (1.756)	1.627 (1.086)
No. of instances of beans or matooke			1.045 (0.800)	0.459 (0.406)	0.619 (0.802)	0.428 (0.413)
Max number of people cooked for lunch or dinner					0.714** (0.322)	0.106 (0.233)
Constant	5.568** (2.272)		5.524** (2.307)		2.012 (2.944)	
Observations	215	215	215	215	215	215
R-squared	0.040	0.036	0.048	0.046	0.074	0.047
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

*The omitted group is households that cooked lunch and dinner not including beans or matooke. 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** (0.729)	0.993 (0.663)	1.758** (0.777)	0.984 (0.747)	1.737** (0.754)	1.011 (0.752)
No. of instances of beans or matooke			-0.00257 (0.280)	0.00787 (0.297)	-0.240 (0.266)	0.0247 (0.300)
Max number of people cooked for lunch or dinner					0.542*** (0.113)	-0.0778 (0.186)
Constant	5.854*** (1.406)		5.854*** (1.407)		3.029** (1.468)	
Observations	357	357	357	357	357	357
R-squared	0.022	0.011	0.022	0.011	0.096	0.012
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

*The omitted group is households that cooked lunch and dinner not including beans or matooke. 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			0.185*** (0.0629)	0.0954 (0.150)	0.172** (0.0771)	0.101 (0.206)
Hours cooked on main stove centered and squared					0.000924 (0.00760)	-0.000213 (0.0144)
Hours secondary stove cooked			0.0378 (0.0623)	0.234 (0.157)	-0.0226 (0.0999)	0.148 (0.248)
Hours cooked on secondary stove centered and squared					0.00694 (0.00761)	0.00878 (0.0192)
Hours main and secondary stove cooked combined	0.117*** (0.0285)	0.162* (0.0825)				
Constant	6.398*** (0.556)		6.330*** (0.569)		6.498*** (0.565)	
Observations	196	196	196	196	196	196
R-squared	0.092	0.034	0.113	0.037	0.118	0.038
Number of household fixed effects		85		85		85

Robust standard errors adjusted for clustering by household in parentheses

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

*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 (125.9)	30.04 (110.8)	150.7 (168.7)	90.13 (125.1)	128.3 (159.0)	76.58 (124.3)
No. of instances of beans or matooke			7.449 (66.26)	-51.37 (49.64)	-26.72 (64.49)	-67.10 (49.80)
Max number of people cooked for lunch or dinner					79.72** (32.34)	62.02** (29.29)
Constant	726.5*** (237.1)		726.8*** (237.9)		352.1* (201.3)	
Observations	362	362	362	362	362	362
R-squared	0.004	0.000	0.004	0.005	0.039	0.026
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

*The omitted group is households that cooked lunch and dinner not including beans or matooke. 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			-17.33 (12.54)	39.32* (20.31)	-20.15 (17.23)	51.24** (25.81)
Hours cooked on main stove centered and squared					0.294 (0.920)	-1.595 (2.120)
Hours secondary stove cooked			24.54 (16.02)	18.24 (20.68)	15.07 (24.26)	17.15 (27.75)
Hours cooked on secondary stove centered and squared					1.148 (1.977)	0.132 (2.670)
Hours main and secondary stove cooked combined	1.775 (7.083)	28.92** (11.08)				
Constant	867.8*** (151.7)		877.6*** (152.4)		901.8*** (163.6)	
Observations	204	204	204	204	204	204
R-squared	0.000	0.054	0.039	0.057	0.042	0.062
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

*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

VARIABLES	(1) OLS	(2) FE
Net wood used with top 5% coding (weight in kg)	45.52*** (17.17)	29.82** (12.47)
Constant	614.2*** (150.4)	
Observations	329	329
R-squared	0.043	0.030
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

*For definitions of variables see Table 1 footnotes.

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