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Inspecting what you expect: Applying modern tools and techniques to evaluate the effectiveness of household energy interventions

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Inspecting what you expect:

Applying modern tools and techniques to evaluate the effectiveness of household energy interventions

by

Ajay Pillarisetti

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the requirements for the degree of

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in

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Development Engineering

in the

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Committee in charge:
Professor Kirk R. Smith, Chair
Professor Michael N. Bates
Professor Daniel M. Kammen

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Abstract

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Doctor of Philosophy in Environmental Health Sciences

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Exposure to fine particles ($PM_{2.5}$) resulting from solid fuel use for household energy needs – including cooking, heating, and lighting – is one of the leading causes of ill-health globally and is responsible for approximately 4 million premature deaths and 84 million lost disability-adjusted life years globally. The well-established links between cooking and ill-health are modulated by complex social, behavioral, technological, and environmental issues that pose unique challenges to efforts that seek to reduce this large health burden. Despite growing interest in the field – and numerous technical solutions that, in the laboratory at least, reduce emissions of harmful air pollutants from solid fuel combustion – there exists a need for refined tools, models, and techniques (1) for measuring environmental pollution in households using solid fuel, (2) for tracking adoption of interventions, and (3) for estimating the potential health benefits attributable to an intervention.

Part of the need for higher spatial and temporal resolution data on particular concentrations and dynamics is being met by low-cost sensing platforms that provide large amounts of time-resolved data on critical parameters of interest, including $PM_{2.5}$ concentrations and time-of-use metrics for heat-generating appliances, like stoves. Use of these sensors can result in non-trivial challenges, including those related to data management and analysis, and field logistics, but also enables novel lines of inquiry and insight. Chapter 2 presents a long-term deployment of real-time $PM_{2.5}$ sensors in rural, solid-fuel-using kitchens, specifically seeking to evaluate how well commonly measured 24 or 48-hour samples represent long-term means. While short-term measures were poor predictors of long-term means, the dataset enabled evaluation of numerous sampling strategies – including sampling once per week, month, or season – that had much lower errors and higher probabilities of estimating the true mean.

Chapters 3 and 4 describe the selection and deployment of 200 advanced cookstoves to pregnant women in rural Palwal District, Haryana, India. Chapter 3 focuses on selection and evaluation of an intervention stove in the community, including preliminary measurement of exposure to $PM_{2.5}$ and CO. These data suggest one method of piloting interventions and exposure assessment methods prior to larger rollouts to ensure community acceptability and feasibility. Chapter 4 specifically addresses adoption and use of the intervention stove over a period of approximately one year through the deployment of data-logging thermometers on 200 traditional and intervention stoves. Intervention stove use declined steadily over time and stabilized after approximately 200 days, while use of the traditional stove remained constant, emphasizing the need for monitoring both traditional and intervention stoves and for monitoring for periods of time beyond just the initial deployment to truly understand use. Chapter 4 additionally investigated intervention stove failures and how well short measures of stove use predict long-term trends (similar to the analysis performed in Chapter 2).

Chapter 5 focuses on utilizing the best available knowledge of exposure-response relationships to estimate the potential health impacts of an intervention at the national level in a software package called HAPIT, the Household Air Pollution Intervention Tool. HAPIT combines background disease data from the 2010 Global Burden of Disease with demographic and socioeconomic data and relative risk estimates from the integrated exposure-response curves to estimate disability-adjusted life years (DALYs) and deaths that could be averted by an exposure-reducing household air pollution intervention. Chapter 5 outlines the methodologies powering HAPIT and contains two example scenarios – one in which open fires are replaced by well-operating chimney stoves, and a second where they are replaced by LPG -- informed by data from the RESPIRE trial and ongoing work in Guatemala.

Chapter 6 synthesizes work from the proceeding chapters and offers suggestions for future lines of inquiry.

To Beth,
my constant companion and muse

To Arri,
my friend, inspiration, and mentor

&

To Amarjit, Anoop, and Sudha,
for their unfailing support

Table of Contents

List of Figures

List of Tables

Preface

The research presented in this dissertation was conducted under the supervision of Professor Kirk R. Smith and the School of Public Health's Graduate Group in Environmental Health Sciences at University of California, Berkeley.

Chapter 2 was modified from a version submitted for publication in *Environmental Science & Technology*[1]. I was the primary author and was responsible for the literature review, data analysis, and manuscript composition. Initial work on this project was started by L. W. H. Alnes. All authors contributed to the editing and revision of the published manuscript.

Chapter 3 was modified from a version published in *Global Health Action*[2]. I was the corresponding author and was responsible for the literature review, all data analysis, and writing of the manuscript. The concept for the paper arose as part of planning for a larger study, described in Chapter 4. Field planning and qualitative data collection was performed by R. Mukhopadhyay and M. Vaswani from the International Clinical Epidemiology Network. All field activities were overseen by N. K. Arora. S. Sambandam and K. Mukhopadhyay led pollutant monitoring exercises at the field site and were overseen by K. Balakrishnan. D. Jack, M. N. Bates, P. L. Kinney, and K. R. Smith assisted in manuscript preparation and pilot study implementation.

Chapter 4 was modified from a version published in *Environmental Science and Technology*[3]. As lead author, I was responsible for the literature review, analysis, modeling, and writing the manuscript. M. Vaswani and N. K. Arora oversaw all fieldwork. All authors contributed to the editing and revision of the published manuscript.

Chapter 5 outlines work done to model the potential health benefits of an intervention stove and was modified from a version published in *Broken Pumps and Promises – Incentivizing Impact in Environmental Health* a forthcoming book edited by Evan A. Thomas, PhD, PE, MPH and published by Springer[4]. As lead author, I was responsible for model construction and evaluation and writing of the manuscript. All authors contributed to the editing and revision of the published manuscript.

Chapters 1 and 6 are unpublished, original works written by the author and edited by the committee members.

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[1] Pillarisetti A, Alnes LWH, McCracken JP, Canuz E, Smith KR. Long-Term $PM_{2.5}$ Monitoring in Kitchens Cooking with Wood: Implications for Measurement Strategies. Submitted to *Environ. Sci Technology* 21 January 2016.

[2] Mukhopadhyay R, Sambandam S, Pillarisetti A, Jack D, Mukhopadhyay K, Balakrishnan K, Vaswani M, Bates MN, Kinney PL, Arora NK, Smith KR. Cooking practices, air quality, and the acceptability of advanced cookstoves in Haryana, India: an exploratory study to inform large-scale interventions. *Global Health Action* **2012**, *5* : 19016

[3] Pillarisetti A, Vaswani M, Jack D, Balakrishnan K, Bates MN, Arora NK, Smith KR. Patterns of Stove Usage after Introduction of an Advanced Cookstove: The Long-Term Application of Household Sensors. *Environ. Sci. Technol.* **2014**, *48*, 14525–14533.

[4] Pillarisetti A, Mehta S, Smith KR. 2015, "HAPIT, the Household Air Pollution Intervention Tool, to evaluate the health benefits and cost-effectiveness of clean cooking interventions." In *Broken Pumps and Promises: Incentivizing Impact in Environmental Health; Thomas, E., Ed.;* Springer International Press.

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Getting through a doctoral program is tough work – for the graduate student, but also for the supporting cast of staff, faculty, friends, and family. A mention on this page is meager compensation to the many people who served as patient mentors and faithful companions on the road to this degree – and from whom I benefitted freely. I am deeply grateful to all of you.

First among them are my parents, Sudha and Amarjit, who helped foster my curiosity and protected my bookish tendencies. Their willingness to let me explore myriad interests, while I imagine bewildering, was invaluable. Thank you for everything. Anoop, bro, your patience with me is astounding, and the dedication and passion you bring to your corner of the cooking world inspires awe. Our rare visits are revitalizing – here's to many more. GPS, your love of the mountains, and the Himalayas in particular, kindled my own – and exposed me to my first open cookfire in a rural home, setting me on this path many years ago.

I wouldn't have made it to Berkeley without the support of Arri Eisen and John Luchhesi at Emory College and Stanley Foster, Anne Riederer, and Jeremy Sarnat at Rollins School of Public Health. Arri, in particular, played a formative role in my time at Emory (and beyond), encouraging me to do research and finding or creating opportunities for us to work together on a range of topics, including a radio show, numerous web projects, and science curriculum for Tibetan monastics. I count myself lucky to consider him a close friend, collaborator, and mentor and draw inspiration from his rare combination of keen scientific insight, empathy, and peerless communication skill.

At UC Berkeley, I am grateful for the opportunity to work alongside Professor Kirk R. Smith, my dissertation chair, whose guidance, intellectual rigor, and openness has been an invaluable inspiration. I blindly emailed Kirk in 2006 looking for contacts in Nepal, to which he graciously replied, kicking off our relationship and this adventure. Thanks to Michael Bates, whose support and consistent thoughtfulness helped hone my dissertation and thinking writ large, and to Dan Kammen, whose perspectives and truly outstanding classes broadened my views on energy issues.

I wouldn't have made it *through* Berkeley without my friends and colleagues – in Environmental Health Sciences and beyond – who enriched my experience and from whom I learned so much: John Balmes, Kalpana Balakrishnan, Ellen Eisen, Darby Jack, Michael Johnson, Sumi Mehta, Sankar Sambandam, Edmund Seto, Donee Alexander, Zoe Chafe, Dana Charron, Jeremy Coyle, Manish Desai, Drew Hill, David Holstius, Nick Lam, Jennifer Mann, Erin Milner, Amanda Northcross, David Pennise, Amod Pokhrel, Ilse Ruiz-Mercado, Lisa Thompson, and Danny Wilson. Thanks to Tracy Allen, Teri Allen-Piccolo, and the whole crew at EME Systems for enabling much of this work and for being a sounding board for ideas small and large.

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To my closest friends – Jim, Gabriel, Eliza, Meg, Ben, Katy, Adam, Em, Charlotte, and Reed – I see and speak with none of you nearly as much as I would like (entirely my fault) – but treasure our moments together. I look forward to many more inevitable reunifications.

Finally, I am thankful for Beth, my fiancée, my love, magooch. I'd be lost without you, awash in a sea of numbers, jargon, and computer maths. Thank you for keeping me grounded, for pulling me from the pale glow of laptop light into the California sunlight, and for being here as a confidant, partner, and friend. I look forward to our future together.

"Not only does cooking mark the transition from nature to culture,
but through it and by means of it, the human state can be
defined with all its attributes..."

Claude Lévi-Strauss, *The Raw and the Cooked*

"Double, double toil and trouble;
Fire burn, and cauldron bubble."

William Shakespeare, *Macbeth, Act iv, Scene 1*

Chapter 1

Introduction

1.1 Background

Globally, approximately 2.8 billion people rely on biomass – including wood, crop residues, and dung – as fuel for cooking.[1] Inefficient combustion of these fuels, often in simple, unvented stoves, results in exposure to hazardous air pollutants responsible for approximately 3.9 million deaths yearly[2], placing it fourth overall and highest in total burden of disease amongst environmental risk factors in the 2010 Global Burden of Disease (GBD-2010).[3]

Studies across the developing world have demonstrated that decreased indoor air pollutant concentrations can be achieved by venting pollution outdoors or by decreasing emissions from the stove.[4-7] Often, these reductions are associated with transitioning from traditional stoves and open fires to 'improved' chimney stoves, which enclose the combustion chamber and move pollution from the kitchen into the outdoor environment. Analyses from the first household energy and health randomized control trial found that chimney stoves failed to reduce emissions, instead simply shifting pollution outside – some of which re-infiltrated the home and some of which remained outdoors.[8] Exposure reductions and health benefits resulting from these stoves, while present, were not of the magnitude expected or desired.

Potential explanations for this lack of exposure reduction include the inability of the intervention stove to adequately drive down emissions and concomitant exposures; the intervention stove being used in tandem with the existing, traditional stove, therein offering attenuated or no exposure benefits; the presence of additional, unmonitored sources of air pollution that may contribute to elevated background concentrations; and chimney interventions solely shifting the pollution from the home to the near-home outdoor environment, where exposure still occurs. Recent stove design innovations focus on decreasing emissions by increasing air flow through the combustion chamber and stabilizing combustion conditions – preventing the release of the pollutants, instead of simply moving them into the near-home environment. Many of these so-called 'advanced cookstoves' show admirable performance at reducing emissions in the laboratory[9] but only mediocre improvements in reducing concentrations of and exposure to health-damaging pollutants in real world evaluations.[10-12] Whatever the reason, the sub-optimal exposure reductions seen in before and after evaluations of various cookstove interventions indicate substantial room for improvement to truly protect health.

Estimating the health benefits of any exposure reduction to particulate air pollution is complicated by highly non-linear 'integrated exposure-response' functions (IERs)[2,13], modeled by Burnett et al (2014) from studies of the relationship between health effects and exposure to particles from ambient air pollution, active smoking, and second-hand tobacco smoke. Given the supralinear shape of the IERs (described in more detail and visually depicted in Chapter 5) for many health effects, including cardiovascular disease, pulmonary disease, and acute lower respiratory infection, the modest exposure improvements provided by chimney and rocket stoves result in relatively small health benefits. Thus, to maximize health benefits, interventions must move exposure significantly 'down the curve' by vastly decreasing emissions and almost completely displacing use of the traditional stove[14].

Despite the limited successes of past stove programs, there is a renewed focus on household energy interventions – enhanced recently by the formation of the Global Alliance for Clean Cookstoves (GACC), spearheaded in 2010 with support from then Secretary of State Hillary Rodham Clinton. Funding from GACC and other governmental and non-governmental agencies has spurred methodological innovations in household air pollution (HAP)-related study design, exposure assessment, modeling, and impact estimation. There is an additional focus in late 2015 on evaluating the potential for truly clean cooking with liquid fuels or electricity to impact health, spearheaded by the United States National Institutes of Health (NIH).

During the last decade, the cookstove evaluation field has benefitted from use of low-cost, high-resolution, high-frequency data loggers based on off-the-shelf sensing technologies. Our research group pioneered the use of these sensors with the development of the University of California, Berkeley Particle and Temperature Sensor (UCB-PATS)[15-17], the Berkeley Aerosol Information Recording System (BAIRS)[18] and the adaptation of commercial iButton technology into the Stove Use Monitoring System (SUMS)[19-21]. We are additionally assisting in the development of new stove use monitors based on low-cost thermocouples, an updated version of the UCB-PATS known as the PATS+, and creation of a low-cost system to evaluate air exchange rates in rural settings known as ARMS (<u>a</u>ir exchange <u>r</u>ate <u>m</u>onitoring <u>s</u>ystem).

The volume of data generated by these sensors allows researchers to better understand variability within and between homes and can draw into question standard exposure assessment practices – including the common use of 24- or 48-hour pollutant measurements as a surrogate for long-term exposures, the practice of short-term monitoring of intervention stove usage to determine uptake and/or adoption, and the necessity of continuous monitoring of both use and measures of pollution. Use of these devices and their data is not without issues, including such challenges as standardized sensor placement, sensor calibration, data handling and analysis and translation of data into meaningful, policy-relevant metrics. The spread of, and challenges arising from, these sensors is, of course, not limited to HAP assessments – findings from other disciplines, including water and sanitation[22,23], ambient air monitoring[24], and climate change offer discipline-specific best practices.

1.2 Key contributions

Leveraging advances in microelectronics, sensors, and data handling and processing – along with greater understanding of exposure-response relationships enabled by the IERs – allows new types of monitoring and evaluation strategies for HAP assessments. The bulk of this dissertation focuses on using this type of highly resolved data to answer questions that hone HAP assessments to maximize field efficiency and to ensure data precision and validity. The techniques employed in this dissertation – and the suggestions arising from my findings – highlight the possibility of using similar methods to better elaborate exposure-response relationships and to drive down uncertainty in our understanding of how an intervention is used and how that use translates to reduced pollutant concentrations in solid-fuel-using homes.

Chapter 2 focuses on the long-term deployment of the UCB-PATS in the Guatemalan Highlands during the Randomized Exposure Study of Pollution Indoors and Respiratory Effects (RESPIRE) randomized control trial. UCB-PATS were deployed for an average of 222 days in 8 households – 4 using an open fire to cook and 4 using a Plancha chimney stove. Minute-to-minute $PM_{2.5}$ concentrations were recorded; this dataset is one of the longest continuous measures of PM concentrations within a developing world kitchen. We use this large volume of data to estimate how much the coefficient of variability (COV, the standard deviation divided by the mean, a measure of dispersion) is reduced by increasing the number of consecutive monitoring days. The paper additionally describes how well short measures – such as a single 24-hour or 48-hour measurement – and alternative measures – such as the mean of measurements made once per study week or study month – predict the long-term average. Findings from the paper have implications for future HAP assessments and strongly suggest that current practices – which rely on short-term measures – are poor predictors of long-term averages and may result in misestimation of potential health impacts.

Chapters 3 and 4 are based on work performed in India, where the disease burdens associated with HAP are particularly pronounced. 85.8% of rural households and 23.3% of urban households rely on either firewood, crop residues, or dung as their primary fuel for cooking. According to the 2011 Indian Census, this accounts for approximately 717 million rural residents and 38.9 million urban residents. GBD-2010 estimated approximately 1 million annual deaths in India attributable to solid fuel use for household cooking – about 10% of national mortality. In terms of DALYs, HAP was the most important risk factor for women and girls and third most important for men and boys in India.

Chapters 3 and 4 make a case for the importance of monitoring usage of both intervention and traditional stoves during interventions. Chapter 3 offers simple guidelines for evaluating the acceptability of laboratory-vetted stoves in a community. It focuses on initial work to identify a feasible intervention and to determine optimal sensor placement and sampling strategies. It includes quantitative and semi-quantitative measures of stove acceptability for two then-widely-available advanced stoves in India. Unlike other chapters in this volume, which are more technical in nature, Chapter 3 focuses on preliminary work necessary to establish the conditions for a stove trial and mirrors the more extensive pilot work done prior to the beginning of the RESPIRE randomized control trial in rural Guatemala and prior to exposure-response work performed in Kenya [25,26]. While it does not offer new techniques or measurements, it emphasizes the importance of pilot work, especially in the context of findings in Chapter 4. This pilot work, while seemingly commonsense prior to any type of large health-related intervention, is still somewhat uncommon in our field. Chapter 3 offers some replicable methods for this type of early work to inform larger, more expensive, and more intensive trials.

Chapter 4 describes new analytic methods for analyzing stove usage data, based on a deployment of the Philips HD4012 (henceforth 'Philips') advanced cookstove to a population of 200 pregnant women in rural North India. The Philips was one of the best-performing biomass-burning stoves in the lab[9] and had been previously tested in India, where it was found to reduce particulate matter and black carbon concentrations.[27] Stove use was assessed by placing small, data-logging iButton™ thermometers (adapted from industries employing a temperature-controlled supply chain) on both intervention and primary traditional stoves, and logging instantaneous temperatures every ten minutes for over one year. While informed by pioneering previous work [19-21,28,29] on stove usage, which described placement, analysis, and modeling techniques, the chapter emphasizes the importance of (1) tracking use continuously over time on both intervention and traditional stoves and of (2) relating stove usage to metrics of energy consumption. It describes the challenges of managing large amounts of data in resource- and staff-constrained environments and of repairing advanced stoves often used beyond recommendations. The chapter also offers new metrics for tracking use and adoption of household energy interventions in a society with complex cooking behaviors. Chapter 4 focuses on the findings from the aforementioned deployment of 200 Philips. Data presented in that chapter are the longest and deepest published study of stove usage to date, with a total of approximately 25 million data points representing 140,000 stove-days. It is also the first published evaluation of a large-scale deployment of an advanced cookstove.

Chapter 5 moves beyond any specific stove type to the larger question of how best to model the health benefits of household energy interventions and to contextualize them in terms of cost-effectiveness as outlined by the World Health Organization's CHOICE (CHOosing Interventions that are Cost-Effective) criteria. The chapter describes the design, development, and underlying theory behind HAPIT, the Household Air Pollution Intervention Tool, and models two example scenarios using empirical data from Guatemala. HAPIT evolved from a simple spreadsheet-based tool to an online platform for evaluating health benefits that incorporates various scales of uncertainty throughout the model. The front-facing simplicity of the tool and its various outputs masks significant 'behind-the-scenes' methodological complexity. HAPIT relies on input data from the Institute for Health Metrics and Evaluation and on up-to-date iterations of the IER curves. It utilizes the IERs to estimate burdens of disease before and after deployment of an intervention and assumes the change in burden after an intervention is an impact of that intervention. HAPIT targets policymakers, program implementers, non-governmental organizations, stove designers, and advocacy groups seeking to evaluate the potential implications of an intervention or to present an array of potential policy solutions to help alleviate the burden of disease associated with solid fuel use for cooking. HAPIT was developed in collaboration with Dr. Kirk R. Smith and Dr. Sumi Mehta, and has benefitted from the input of numerous colleagues and collaborators globally.

1.3 Context

A framework commonly used to contextualize environmental health sciences (EHS) research writ large is the environmental health pathway, which links pollutant sources to health endpoints through a linear progression. An introduction to and application of the EHS pathway to the chapters of this dissertation helps clarify and contextualize its place in the broader household energy literature.

The environmental health pathway describes a step-ordered, linear relationship between a source of pollutants and health effects (depicted in Figure 1.1, adapted from a figure from Smith et al [30]). Between the source and health effects are environmental components – emissions of a pollutant into the environment per unit time and concentration in the environment, expressed in terms of mass of pollutant per volume or mass of environmental media – and organism-level components, including the biologically relevant portion of an exposure and concomitant health effects. The bridge between the environment and the human is exposure, which is a combined measure of duration and intensity of contact with a given pollutant in a given environment.

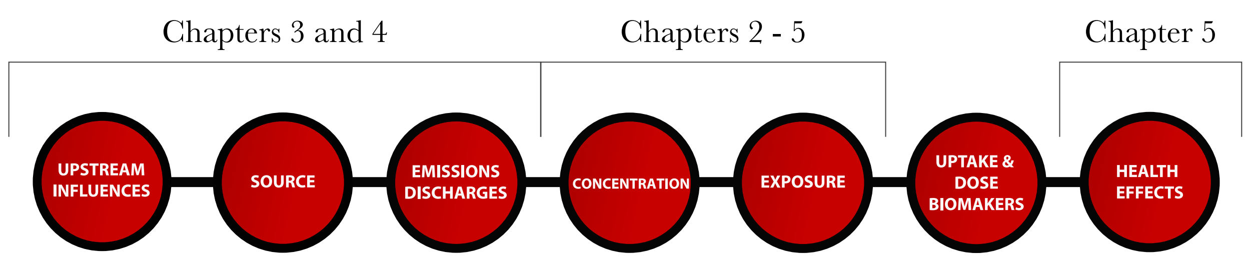


Figure 1.1 Linear Environmental Health Pathway
This depiction of the Environmental Health Pathway, based on an earlier formulation by Smith et al (1987), includes indicators of which chapters of this dissertation pertain to which components of the pathway.

Chapter 2 of this dissertation focuses on measurements of $PM_{2.5}$ concentrations in rural Guatemalan kitchens to provide strategies to better estimate annual concentrations and exposures. Chapter 3 provides preliminary measurements of $PM_{2.5}$ and CO exposures in rural Haryana. Chapters 3 and 4 both focus extensively on stove usage, which modulates two relationships on the pathway: the relationship between a user and a source and the relationship between emissions from sources and concentrations and exposure. Chapter 3 offers some suggestions on how to understand what influences the choice of an intervention stove and what drives use of a specific household cooking appliance, while Chapter 4 focuses on methods to more precisely quantify usage of multiple sources. Chapter 5 links measured and modeled exposures with health effects through the IERs.

Chapter 2

Long-term $PM_{2.5}$ monitoring in kitchens cooking with wood: implications for measurement strategies

2.1 Background

As described in Chapter 1, forty percent of households globally rely on solid fuels – including wood, dung, grass, coal, and crop residues – for cooking.[1] The Comparative Risk Assessment (CRA), a component of the Global Burden of Disease (GBD-2010), estimated that in 2010 household air pollution (HAP) resulting from the combustion of these fuels was responsible for 3.9 million premature deaths, accounting for ~4.8% of global disability-adjusted life years (DALYs) lost.[2,3] Most evidence of these health effects is from studies using either measured or modeled surrogates of individuals' typical or long-term (months to years) particle exposures, such as fuel type or kitchen concentrations.

Measures of particulate matter with an aerodynamic diameter of less than 2.5 microns ($PM_{2.5}$) are central to cookstove intervention program evaluations[7,31,32,33,34,35] and global health assessments[36] related to solid fuel use. Many of these studies use sampling durations of either 24 hours[10,33,37,38] or 48 hours[7,31,32,39], which we refer to here as short-term measures. It is unknown how well these short-term measures predict annual concentrations or exposures.

Although many studies have measured $PM_{2.5}$ concentrations in village homes, few have measured repeatedly. In Mexico, during an assessment of the Patsari cookstove, $PM_{2.5}$ kitchen concentrations were monitored for 4 days in 24 homes.[40] Researchers observed that variability decreased as the number of sampling days increased; however, they were unable to compare this to a long-term mean, such as an annual average concentration. In Guatemala, researchers compared single 48-hour personal carbon monoxide (CO) measurements to the long-term mean of 4 repeated measures. They found that the single measures were unreliable as an estimate of long-term exposure.[41]

Use of short-term measurements introduces classical measurement error in exposure, which attenuates estimates of the true exposure-response relationship. Lengthening the duration and/or frequency of measurements is a potential solution to this problem, but brings additional equipment and personnel costs, increases field-worker burden, and lengthens study procedures in homes, impacting participants.

As part of the RESPIRE (Randomized Exposure Study of Pollution Indoors and Respiratory Effects) randomized control trial[8,42] , which evaluated the impact of reduced exposure to wood smoke on childhood acute lower respiratory infections, we placed particle monitors in homes with and without intervention chimney stoves (Figure 1) and monitored daily $PM_{2.5}$ concentrations for on average 200 days per home. The current study seeks to determine how accurately a single 24- or 48-hour measurement predicts long-term concentrations and to quantify gains in precision from alternate sampling strategies – including increased measurement duration over consecutive days and repeated 24- and 48-hour samplings over time.

2.2 Methods

Study location and population

Measurements were made between February 2004 and March 2005 in 8 households located in the western highlands of Guatemala (altitude 2200 – 3300 meters). The region has a temperate and fairly consistent climate (Appendix Figure B1) with three seasons: dry and cold (November through February), dry and warm (mid-February through April), and rainy and warm (May through October). The selected households were a convenience sample of RESPIRE control and intervention homes. Control homes cooked with a traditional open fire (n=4); intervention homes had a chimney stove known locally as the Plancha (n=4). All participants had relatively similar household characteristics and used wood as their primary cooking fuel. RESPIRE project details – including human subjects approvals, consent, survey details, recruitment procedures, and information about the intervention, were reported previously[8].

$PM_{2.5}$ measurements

Continuous $PM_{2.5}$ measurements were made using the University of California, Berkeley Particle and Temperature Sensor (UCB-PATS, Berkeley Air Monitoring Group, USA) following standard protocols.[15,34] The UCB-PATS is a data-logging, battery-powered optical particle monitor created using custom microelectronics coupled with commercial smoke alarm sensing technology. The device is powered by a 9V battery and was set to log photoelectric responses every minute. A total of 48 unique UCB-PATS were rotated through households during this study. All monitors were assigned the same temperature and particle coefficients used to convert raw photoelectric responses into particle concentrations in micrograms per cubic meter. Masses reported by the UCB-PATS were adjusted, using a pooled $PM_{2.5}$ gravimetric correction factor

Figure 2.1 Typical intervention and traditional stoves in San Lorenzo, Guatemala
The top panel depicts the Plancha intervention stove in San Lorenzo, Guatemala. Fuel is fed into an enclosed combustion chamber (not visible); smoke vents out through a chimney (near the rear of the stove). The lower panel depicts a typical open fire cookstove.

determined during a previous study[15] amongst wood-burning households in Guatemala. Unadjusted values and gravimetric correction factors are reported in Appendix Table B1.

All UCB-PATS were zeroed in a resealable plastic bag for 30 minutes before and after deployment in the households. Monitors logged data every minute and were placed at a height of 1.5 meters from the floor of the kitchen and from windows and doors and 1 meter from the combustion zone of the primary stove. Fieldworkers visited participating homes every week to swap monitors. Monitors that were removed from homes were transported to the field headquarters, where data were downloaded and routine monitor maintenance was performed. Logs of household visits and monitor performance were maintained.

The daily mean concentration was calculated for each household on days with less than 10% of data missing. Additionally, because we are interested in predicting long-term daily averages, we excluded periods associated with unusual events. In one household, kitchen renovation began in January of 2005; all measurements in this home after Dec 31, 2004, were excluded. At the end of RESPIRE, all control household received the chimney stove; measurements in these four homes after introduction of the intervention were excluded. Finally, one outlier day was excluded, during which the mean concentration exceeded the next highest day by greater than 2-fold.

Quantifying the COV with increasing measurement durations

We calculated the reduction in the coefficient of variation (the standard deviation divided by the mean) for consecutive days of measurement [40]. We selected 10 random days as starting points from the complete pool of valid measurement days and estimated the COV for sampling periods of 1, 2, 3, 4, 5, 6, 7, 14, 21, and 28 days from the starting point. To ensure stable estimates, this process was repeated 1000 times; the average COV is reported.

Evaluating sampling strategies

To evaluate how well measures of various lengths predicted the long-term household mean concentration, we calculated the mean of every possible set of consecutive days of measurements (of 1, 2, 3, 4, 7, 14, 21, and 28 days), the mean of a single 24-hour measurement drawn once per study week and once per study month, and the mean of 48-hour samples drawn once per season. For each set of measurements of varying length, we determined how many estimates fall within a given precision level – for instance, within 20% of the long-term household mean concentration – and divided by the total number of estimates, yielding the probability of a random measurement of a specific duration falling within a given range around the long-term mean. Calculations were performed separately by household and are presented in aggregate by stove type. We additionally calculated the root mean square error (RMSE) and its standard deviation for each measure described above.

Explaining variability in $PM_{2.5}$ concentrations with mixed models

We used linear mixed effects models to partition within and between household variances. The base mode took the following form:

$$Y_{ij} = \beta_0 + b_i + e_{ij}$$

where Y_{ij} is the i^{th} concentration in household j, β_0 is the overall intercept, b_i is the random effect for household i, and e_{ij} is the leftover error. By comparing the base model with models of increasing complexity, we estimated how much variability in daily average $PM_{2.5}$ concentrations could be explained by fixed, household-level characteristics, such as stove type, socioeconomic indicators, and home characteristics and by time-varying effects, such as day of week and season[41]. We additionally evaluated the autocorrelation between consecutive measurement days.

Fieldworker time and cost

We evaluated the financial and person-time impact of the various sampling strategies described above. Time requirements were estimated based on the field manager's experience with the particle monitors. Cost data was derived from study budgets.

All statistical analyses were performed in R 3.1 (R Foundation, Vienna, Austria).

2.3 Results

$PM_{2.5}$ measurements

Approximately 2.4 million data points were recorded during 1634 valid measurement days. The number of days measured per home ranged from 120 to 333 days. The average daily concentration was 1903 μg/m^3 (SD = 1335) in open fire homes and was 125 μg/m3 (SD = 133) in chimney stove homes. Summary statistics by household are described in Table 2.1; time series plots by stove-type and household are presented in Figure 2.2. Both the summary statistics in Table 2.1 and graphs in Figure 2.2 indicate wide variability both within and between households in each group. Correlation between consecutive days of measurement is shown by household in Appendix Figure B2 and in aggregate in Appendix Figure B3. Comparisons with relevant global studies are in Appendix Figure B4 and B5.

Table 2.1 Mean $PM_{2.5}$ concentrations in μg/m^3 by household and stove type

	N	Mean	SD	Min	Median	Max	Start Date	End Date
Open Fire	136	2255	1068	528	2076	5987	7/7/04	12/13/04
Open Fire	134	1118	592	102	981	2903	7/7/04	12/12/04
Open Fire	120	923	494	194	863	3135	2/17/04	7/16/04
Open Fire	215	2717	1514	53	2476	9017	2/24/04	11/22/04
All Open Fire	**605**	**1903**	**1335**	**53**	**1557**	**9017**		
Chimney Stove	154	143	119	39	115	1077	7/7/04	12/31/04
Chimney Stove	215	147	138	41	98	1342	7/7/04	3/21/05
Chimney Stove	333	54	77	31	41	1122	2/17/04	3/21/05
Chimney Stove	327	175	149	43	128	975	2/17/04	3/21/05
All Chimney Stove	**1029**	**125**	**133**	**31**	**84**	**1342**		

Figure 2.2 Daily mean $PM_{2.5}$ concentrations in μg/m³
The top panel displays data from intervention homes. The lower panel displays data from open fire homes. The dotted lines are the study-wide means by stove type.

Coefficient of Variation (COV)
Figure 2.3 displays the reduction in the coefficient of variation associated with longer consecutive measurement days. Most of the reduction in COV occurs by increasing the measurement duration up to 1 week; additional reductions continue to occur, but the rate of reduction decreases. Notably, chimney stove measurements are more variable than open fires, albeit around a much lower mean.

Evaluating sampling strategies
Comparisons of the precision of samples of varying durations are displayed graphically in Figure 2.4 for both open fires and chimney stoves. Approximately 32% of chimney and 39% of open

fire 24-hour samples are within 25% of the long-term mean. Increasing the consecutive days of measurement led to increases in precision for both stove types. The magnitude of the increase varied; open fire homes saw greater increases in precision for an equivalent increase in sampling length.

Table 2.3 depicts the probability of falling within 50%, 25%, and 10% of the long-term mean for each of the sampling strategies. Probabilities increase with increasing consecutive days of measurement; sampling once per study week (20 times per household in the current study) or once per study month (6 times per household in this study) greatly improve the probability of attaining precision goals, as does selecting 48-hour samples randomly once per season. Under all scenarios, samples are less likely to fall within precision goals for the chimney stoves.

The RMSE for each sampling strategy is displayed in Figure 2.5 and described in Appendix Table B2. Samples composed of a smaller number of days have more dispersed RMSEs, as indicated by the error bars representing one standard deviation above and below the central estimates. The RMSEs ranged from 27 – 110 μg/m³ for chimney stoves (20 – 85% of the overall chimney stove mean) and 168 – 1000 μg/m³ for open fires (10 – 50% of the overall open fire mean). For both stove types, the largest RMSE was for a single sampling day, while the smallest was for the mean of random days selected from each study week.

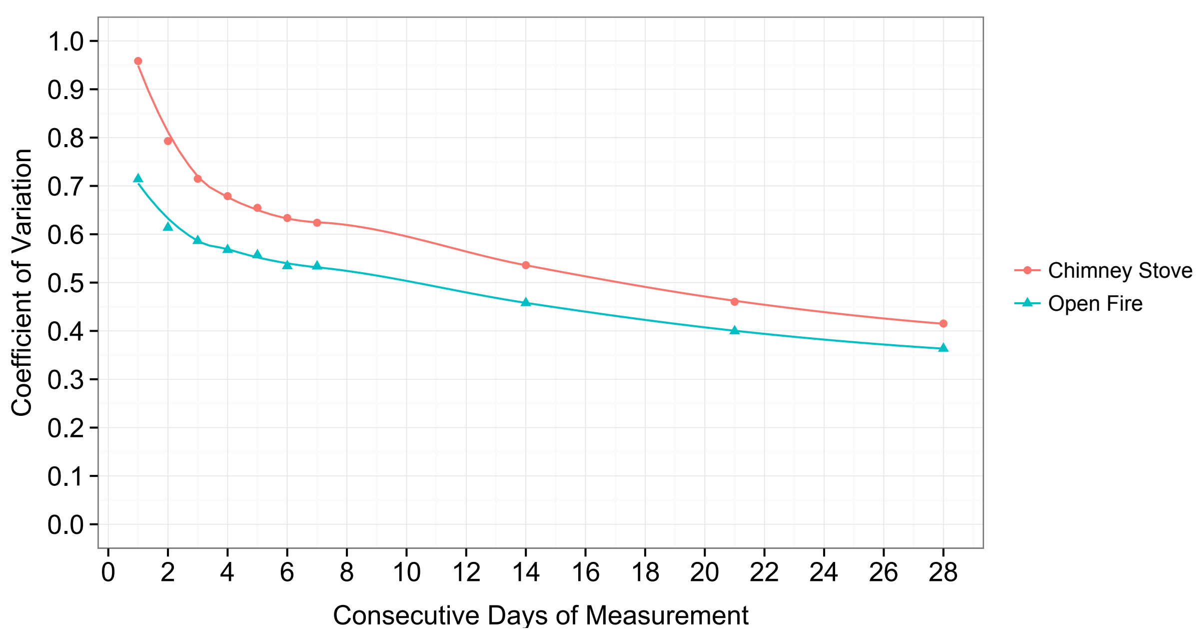


Figure 2.3 COV with increasing consecutive days of measurement
COVs are reported above each measurement periods of 1, 2, 3, 4, 5, 6, 7, 14, 21, and 28 consecutive days were evaluated.

Explaining concentration variability

Mixed models evaluated during this analysis are shown in Table 2.3. Model (A) is the simplest model, containing no covariates; model (D) is the most complex, containing both fixed and time-varying covariates. A variable for stove type explained the majority of the between-household variability; addition of other fixed and time-varying variables explained little or no additional variability, consistent with previous modeling work in this community in Guatemala[41].

Table 2.2 Mixed model variance components for mean $PM_{2.5}$ concentrations

Model		Within-household variance	Between-household variance	$\boldsymbol{R^2_{within}}$ A	$\boldsymbol{R^2_{between}}$ B
A	$Y_{ij} = \beta_0 + b_i + e_{ij}$	0.33	2.25		
B	$Y_{ij} = \beta_0 + \beta_1(Stv) + b_i + e_{ij}$	0.33	0.26	0	0.88
C	$Y_{ij} = \beta_0 + \beta_1(Stv) + \beta_2(X)_i + b_i + e_{ij}$	0.33	0.32	0	0.86
D	$Y_{ij} = \beta_0 + \beta_1(Stv) + \beta_2(X)_i + \beta_3(Z)_{ij} + b_i + e_{ij}$	0.32	0.30	0.03	0.86

[A] Within household variance explained by model relative to baseline model (A).
[B] Between household variance explained by model relative to baseline model (A).
Model C contains the following time invariant variables (X): an asset index, roof type, wall type, and kitchen volume.
Model D contains time varying variables (Z) day of week and season.

An additional model (not shown) containing a random intercept term for UCB monitor explained approximately 3% of the within household variability relative to the baseline model. A fourth order autoregressive correlation structure was fit given the autocorrelation observed between mean concentrations over consecutive days in the data (Appendix Figure B2 and B3).

Fieldworker time and cost

Sampling design decisions depend on the desired precision and confidence of field measurements in light of cost and personnel limitations. For this study, field workers were paid 65 Guatemalan Quetzals per day (approximately 8.45 USD at the midpoint of the study) for 8 hours of work, which was above the minimum wage at that time. A single monitor deployment – including launching and zeroing the device in the lab before and after sampling and traveling to and from participating households, but excluding data download – required approximately 2 hours of fieldworker time during this study. The data download time was estimated at 5 minutes per sampled day. For deployments greater than 1 week, we assumed fieldworkers would have to visit homes once per week to maintain the monitors, requiring approximately 1 hour. We assumed that a deployment for a 24-hour period took 2.08 hours and cost 2.2 USD. Table 2.4 includes cost estimates of each sampling strategy per household.

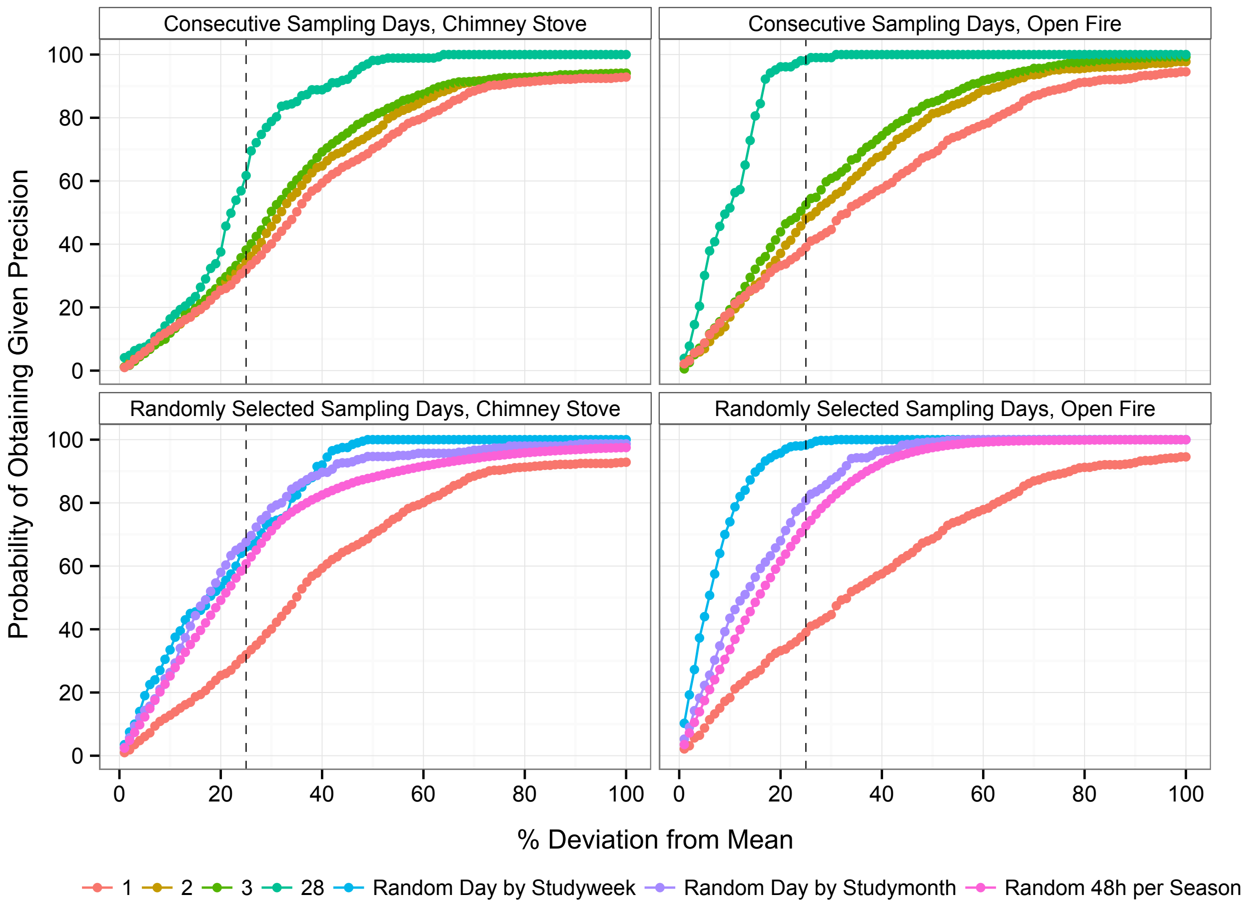


Figure 2.4 Changes in precision given sampling intervals of different lengths
The x-axis represents the deviation from the long-term mean; the y-axis is the probability of obtaining a measurement at a specific percent deviation from the long-term mean. The top panels are for consecutively sampled days; the lower panels are for randomly selected sampling days. The stove type is specified in the panel title.

Table 2.3 Probability of being within 10, 25, and 50% of the long-term mean

Precision Level		50% (least stringent)		25%		10% (most stringent)	
Sample	Days in sample	Open Fire	Chimney	Open Fire	Chimney	Open Fire	Chimney
Randomly selected days		Probability					
1 day	1	69%	70%	39%	32%	18%	13%
1 day per study month	6	99%	95%	81%	68%	44%	27%
1 day per study week	20	100%	100%	98%	66%	74%	34%
48 hour period per season	6*	97%	88%	72%	61%	33%	26%
Random consecutive days		Probability					
2 days	2	81%	75%	48%	34%	17%	13%
3 days	3	85%	80%	53%	38%	19%	12%
4 days	4	89%	82%	56%	41%	24%	14%
7 days	7	96%	82%	64%	48%	24%	14%
14 days	14	99%	82%	79%	54%	36%	13%
21 days	21	100%	93%	88%	52%	47%	17%
28 days	28	100%	98%	98%	62%	51%	16%

* This strategy, while comprised of 6 days of measurements, requires three 48-hour deployments.

Table 2.4 Cost and fieldworker time commitment per household

Sample	Sampling Days	Fieldworker time (minutes)	Data download time (minutes)	Total Time (hours)	Cost per home over sampling period ($)*
Randomly selected days					
1 day	1	120	5	2.1	2.2
1 day per study month	6	720	30	12.5	13.2
1 day per study week	20	2400	100	41.7	44.0
48 hour period per season	6	360	30	6.5	6.9
Random consecutive days					
2 days	2	120	10	2.2	2.3
7 days	7	120	35	2.6	2.7
14 days	14	205	70	4.6	4.9
21 days	21	330	105	7.3	7.7
28 days	28	435	140	9.6	10.1

* Cost per home was calculated as the total time divided by 8 (the number of working hours per day) times the daily wage of 8.45 USD per day.

2.4 Discussion

We report on the largest dataset of repeated measurement of $PM_{2.5}$ concentrations in households using solid fuels for cooking to date. By deploying real-time monitors routinely for an extended period of time, we were able (1) to describe the variability in $PM_{2.5}$ concentrations in rural Guatemalan homes using either an open-fire or a chimney stove, (2) to estimate how well traditionally performed short-term measures predict long-term averages, and (3) to suggest alternative sampling approaches to better predict the long-term mean.

The small sample size in each stove group limited the range of statistical modeling we could perform. Descriptive analyses (Appendix Figures B4, B5, and B6) indicate little difference in the distribution of $PM_{2.5}$ concentrations by season and day of the week both when all households were pooled and when they were examined individually. This is consistent with previous findings from other studies[21,41], in which stove usage and personal exposures to carbon monoxide were found to be largely consistent throughout the year for this population. We additionally note that measurements closer in time were correlated, though the cause of this correlation is unknown. Although seasonal effects were significant in the previous stove usage analysis[21], the magnitude of modeled effects was small (seasonal differences ranged from 3 to 5%). We expect more seasonal variability in kitchen $PM_{2.5}$ in regions with more varied seasons and different cooking and

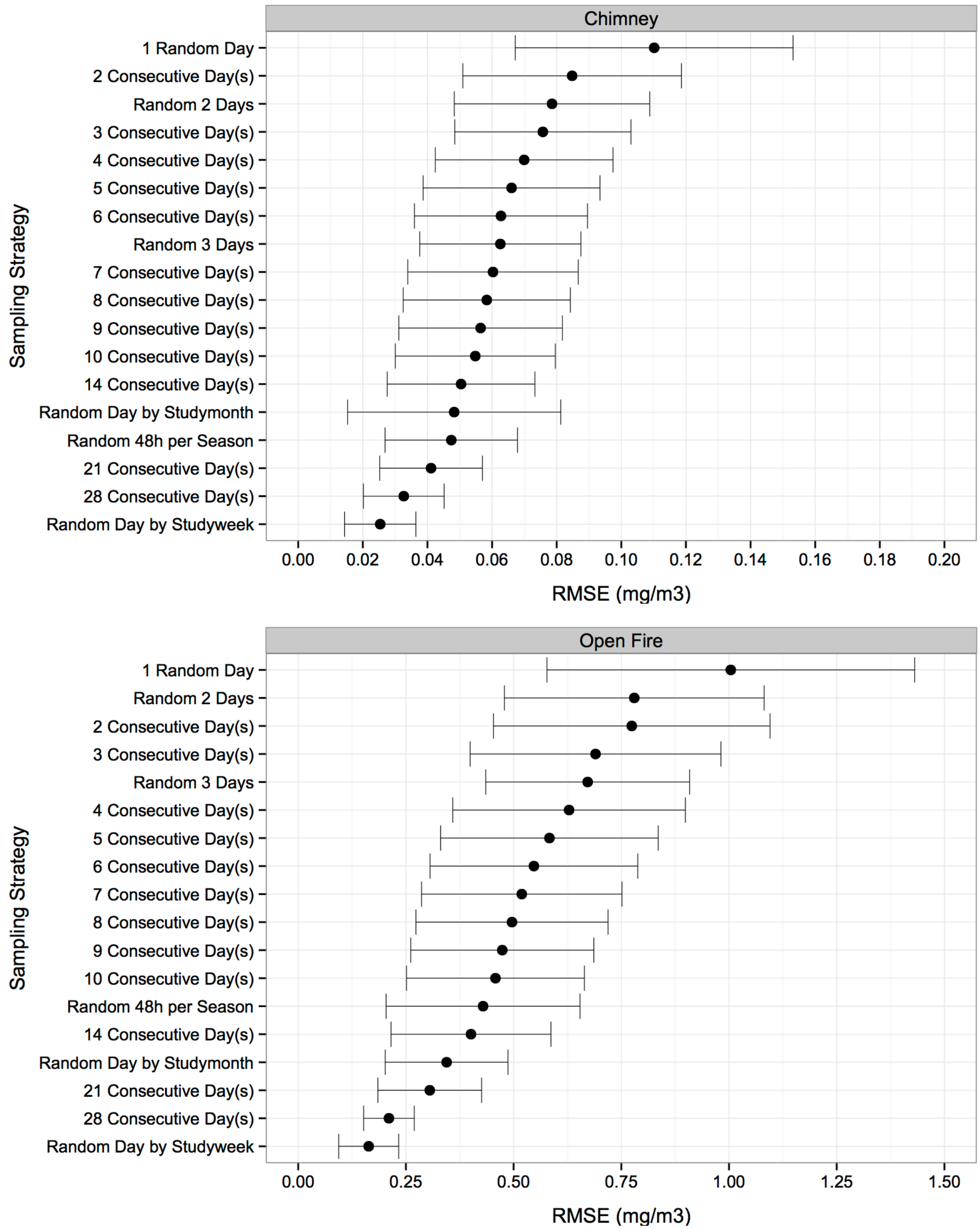


Figure 2.5 RMSE of sampling strategies relative to the long-term mean
The x-axis is the error; the y-axis is each sampling strategy. Error bars are the mean RMSE ± SD. The top panel is for chimney stoves; the lower panel is for open fires.

heating patterns. Similar analysis to the one reported here should be repeated in these environments to discover if a strategy that samples once for 24 hours per study week or study month or once for 48 hours per season could also produce better estimates of long-term average concentrations, as reported here.

Coefficient of Variation

A study in the central highlands state of Michoacán, Mexico[40], found that the COV was reduced from 0.68 for a single, 24-hour measure to 0.48 when the sampling duration was increased to 96 hours. The majority of the reduction in COV occurred by increasing the duration of sampling to 48 hours. Our findings were similar; the COV was reduced from 0.96 to 0.78 for chimney stove homes and from 0.71 to 0.61 for open fire homes during the first 48 hours. By 96 hours, the COV in our study reduced to 0.68 and to 0.57 for chimney and open fire homes, respectively. In both Mexico and the current study, the COV decreased by 29% over the first four days. Figure 2.3 indicates that the COV begins to stabilize at monitoring durations of approximately 1 week. The higher COV in chimney-stove homes may indicate occasional open fire use, a phenomenon known as stove stacking[28,43], the well-documented practice of using multiple stoves in a home. In areas where several stoves are used, it is likely that estimation of long-term concentrations using a single 24-hour measure will be imprecise. Inspection of $PM_{2.5}$ traces measured during this study which had an average concentration over 1 mg/m^3 indicated periods of cooking from sources other than a chimney stove by visual inspection (data not shown). While this type of inspection is possible, objective monitoring using stove use monitors (discussed below) is preferred.

Sampling strategies

Short-term measurements of 1 or 2 days had a low probability of closely estimating the long-term mean. Increasing the measurement duration to greater than 7 days increased the probability of falling within 25% of the long-term mean and reduced the RMSE. Alternate sampling strategies – that focus on sampling once per study week or once per study month – improved the probability of falling within any given deviation from the long-term mean and also reduced the RMSE. However, these strategies require additional resources and incur added costs and impositions on participating households. Increasing the measurement duration to 48 hours and sampling three times offers a compromise between error and the burden imposed on households and on fieldworkers by extra measurement visits. The larger error across strategies in chimney stove households may be due to continued, possibly occasional, usage of the old stove or simultaneous use of both stoves, leading to less consistent concentrations when a small number of days are selected from the complete set of available days at random.

Limitations and future work

This analysis had a number of limitations. First, the study had only 8 participating households. The disadvantages of having only 4 households in the chimney-stove and open-fire groups were partially alleviated by many repeated measures.

The excellent relationships between households and researchers in this community enabled placement of monitors for many months and repeated visits by field workers. This rapport, built over years of work in Guatemala, may not be replicable in other settings and may limit the reproducibility of the current study. Local cooking and heating customs differ amongst solid fuel-using households globally. Replication in additional geographies will further help determine the best approaches for optimizing sampling strategies.

For many health outcomes associated with exposure to $PM_{2.5}$ resulting from solid fuel use for cooking, there are exposure durations of interest that are longer than the total duration measured for this study. For example, to understand effects of exposure on chronic obstructive pulmonary disease or cardiovascular disease, we would ideally measure exposure over decades. Although our study informs the viability of using short-term measure to predict annual means, it cannot address variability in exposures over these decadal timeframes. Our study additionally cannot comment on short-term peak concentrations, which can be of concern for women and children [26,44]. Finally, there are concerns about other PM size distributions (like ultrafine particles), particle characteristics (like black carbon), and chemical composition that may impact health. Similar measurement-related concerns exist for these pollutants but should be addressed separately.

Data from the UCB monitors used during this study were not individually gravimetrically adjusted, instead relying on a pooled correction factor from previous work[15]. As a result, the coefficients used to convert raw millivoltage from the photodetector into PM mass may misestimate the true concentration; however, we expect the relative differences between monitors remained constant. Concentrations reported in Table 2.1 are thus indicative of the variability within and between homes, but estimates of actual indoor concentrations of pollutants may deviate from true values.

We were unable to measure several time-varying factors that may impact kitchen $PM_{2.5}$ concentrations, including use of multiple stoves, weather near households, changes in household configuration, and changes in the number of people per household. Advances in the ability to monitor stove usage using small, data-logging thermometers (Stove Use Monitors – SUMs) should help better understand the variability of $PM_{2.5}$ concentrations within homes, especially in homes where multiple stoves are being used. In instances where stove use is not correlated with concentrations and exposures, additional unmeasured sources should be considered. Similarly, any future studies of long-term pollutant concentrations in biomass-burning households should capture information – such as behavioral changes due to lifecourse events, like pregnancy or delivery, or changes in household structure – that may help explain the variability within and between households. These types of changes, which were not measured for this analysis, may be important for analyses looking at specific maternal and child health outcomes, and should be collected in addition to routinely collected information, including the number of household members in a home, special cooking done during monitoring periods, changes in fuel source, and stove-fuel-food combinations that may change with season.

Our simple estimate of program costs does not take into account monitor availability or pricing. Up-front equipment costs can be high; the availability of monitors to perform measurements of concentration or exposure depend on program resources and vary widely. Additionally, our cost estimates may slightly over-estimate the per sample fieldworker cost; presumably, during long-data download sessions, field staff could perform other tasks. Finally, advances in monitoring technology should dramatically drive down the time required to download data and manage devices.

Under ideal circumstances, health researchers would repeatedly measure personal exposure, tracking individuals through space and time, in place of measuring kitchen concentrations, as done in this study. During data collection for the current study, such ongoing monitoring was not possible due to the project cost and participant burden of personal exposure assessment. Optimizing the duration of sampling for exposure assessments is not straightforward, however. We reviewed published exposure measurements (Appendix Tables B3 and B4) and extracted the mean and standard deviation of exposures to estimate COVs, which varied widely depending on locale and pollutant measured.

For $PM_{2.5}$ exposure measurements at our field site in Guatemala, the estimated COVs were 1.13 for open fires and 1.27 for chimney stoves[45] − higher than the COV for a single kitchen measurement reported here (0.71 and 0.96 for open fires and chimney stoves, respectively). Contrastingly, in a Honduran community using a mixture of stoves, the COV from personal exposures to $PM_{2.5}$ was lower than that of kitchen concentrations (0.9 and 1.4, respectively)[46]. In a Ghanaian community using primarily open fires, personal measurements also had a lower COV than kitchen measurements (0.61 and 0.92, respectively)[47]. This variability may be related to cooking styles and practices, difference among roles of household members, and other behavioral factors, as well as structural differences in household environments, and indicates the need for more evaluation of personal exposure measurement duration.

2.5 Conclusion

As part of pilot work for future large-scale studies, investigators may wish to consider small, targeted long-term monitoring studies along the lines of what we report here, which could leverage recent advances in particle monitors to potentially require less frequent field visits than the one-week interval we employed. These could better quantify exposure variability in different situations by monitoring households and individuals for a number of consecutive days. Such studies could greatly increase the efficiency of the sampling strategy employed in the study being planned, whether to conduct exposure-response analysis of health outcomes or to assess the pollution impacts of interventions, as well as help decide more mundane, but important, questions such as whether monitoring on weekends is needed.

The choice of sampling strategy is motivated by a number of competing factors. First, there are considerations of logistical issues, such as the study budget, the cost of monitoring equipment, the availability of study staff, and the burden on participants. Second, there are analytical issues, such as whether the question of interest involves group-level estimates, which are unbiased and relatively constant, regardless of monitoring duration; or individual estimates of exposure, which are imprecise when estimated from short-term measurements of pollutant concentration. Most studies of household air pollution focus on a single measurement period of either 24 or 48 hours. Our findings suggest that if short measurement durations are used to link air pollutant concentrations and exposures to ill-health, the true effect size will be underestimated. Measurement durations (1) longer than 48 hours or (2) consisting of repeated 24 or 48 hour measurements throughout a study should be considered in future studies of household air pollution to accurately characterize variability and to better predict long-term concentrations and exposures.

Chapter 3

Traditional cooking practices, air quality monitoring, and the acceptability of advanced biomass cookstoves in Haryana, India: An exploratory study to inform planning of large-scale intervention efforts

3.1 Background

According to the 2011 Indian census, approximately 66% of all households rely primarily on wood, crop residues, or cow dung for energy [48]. This comprises 23% of urban households and 86% of rural households. Approximately 780 million Indians living in 160 million households relied primarily on these fuels for their cooking needs [48,49]. In 2009, the Indian Ministry of New and Renewable Energy (MNRE) announced the National Biomass Cookstove Initiative, which seeks to "achieve the quality of energy services from cookstoves comparable to that from other clean energy sources, such as LPG" [50].

Capitalizing on renewed interest in India and beyond to identify interventions to reduce exposures to household air pollution, we sought to evaluate different dissemination approaches for a national advanced combustion stove program. In this chapter, I describe an exploratory study to design a conceptual framework for a Newborn Stove (NBS) Initiative targeted at pregnant women who access the national public antenatal care system. The specific aim of the larger initiative was to introduce advanced combustion biomass stoves through the antenatal care system in order to reduce the prevalence of adverse pregnancy outcomes, especially low birth weight, a serious problem in India today. The idea of a NBS study sought to target the most vulnerable – poor, pregnant women – during a period of time when significant exposure reductions could have a meaningful impact on the health of the developing fetus.

As approximately 75% of the nearly 27 million births in India each year include at least one antenatal care visit [51], a national program adding an advanced stove to the package of antenatal care benefits could cover a major portion of the country's most vulnerable households within a few years. Importantly, a stove intervention disseminated via the public antenatal care system could be highly specific in reaching poor, pregnant women, nearly all of whom use biomass fuels for cooking. Pregnant poor women are arguably the largest easily identified vulnerable group for HAP interventions. Middle- and high-income women, who commonly use gas for cooking, would not be part of this proposed program.

A recent meta-analysis indicates that a truly advanced stove − one that brings HAP exposures close to those of clean fuels, particularly gas − might be able to achieve on average a 93 gram increase in birth weight [52]. This would be a major improvement in India, where about 30% of babies are born underweight (<2500 g) [53]. To show the actual improvement in practice, however, will likely require a major cluster-randomized trial of the type historically required before public investment in large-scale national programs, such as for vaccines.

To obtain data needed to design such a large NBS trial, we initiated a study in Palwal district, in the State of Haryana, India, to assess the feasibility of distributing advanced combustion cookstoves through the public antenatal care system. It enrolled 200 pregnant women and assessed usage patterns of traditional and advanced combustion cookstoves and measured HAP before and after introduction of the advanced stoves. The study also gathered data on user perceptions and acceptability of the advanced stoves and assessed the feasibility of capturing gestational age and birth weight in rural Indian communities.

This chapter describes the exploratory work for the design of this study that (1) characterized traditional cooking practices in the study communities, (2) compared different methods for monitoring air pollution levels associated with traditional cooking practices and established baseline air pollution levels associated with these practices, (3) evaluated the cultural acceptability of two commercially available advanced combustion cookstoves through semi-structured interviews, (4) tested methods to objectively monitor advanced stove usage, and (5) evaluated the feasibility of assessing personal exposures to combustion byproducts among pregnant women.

3.2 Methods

Study location

The work in this chapter was undertaken at the INCLEN (International Clinical Epidemiological Network) SOMAARTH demographic and environmental surveillance site, located in Palwal District, Haryana, approximately 80 kilometers south of Delhi. Palwal district has an area of 1,367 square kilometers and a population of approximately one million [48]. The surveillance site includes a population of approximately 200,000 from 51 villages across 3 administrative blocks of Palwal, encompassing 308 square kilometers. The villages selected for this preliminary assessment use predominantly wood and cow dung for cooking and have access to electricity periodically throughout the week. From the villages in the SOMAARTH site, convenience samples were drawn for each of the three distinct components of the current study (Figure 3.1).

Assessment of traditional cooking patterns
In-depth, semi-structured interviews with primary cooks in 32 households in 23 SOMAARTH villages were conducted and analysed by a trained anthropologist from INCLEN, using a questionnaire developed by University of California, Berkeley. Primary cooks were those that prepared 50% or more of the meals in the previous week. The interviews began with a consent process and an explanation of the purpose of the study. Questions were derived from a literature review and tailored to meet our specific research aims. Interviews were conducted in Hindi and digitally recorded.

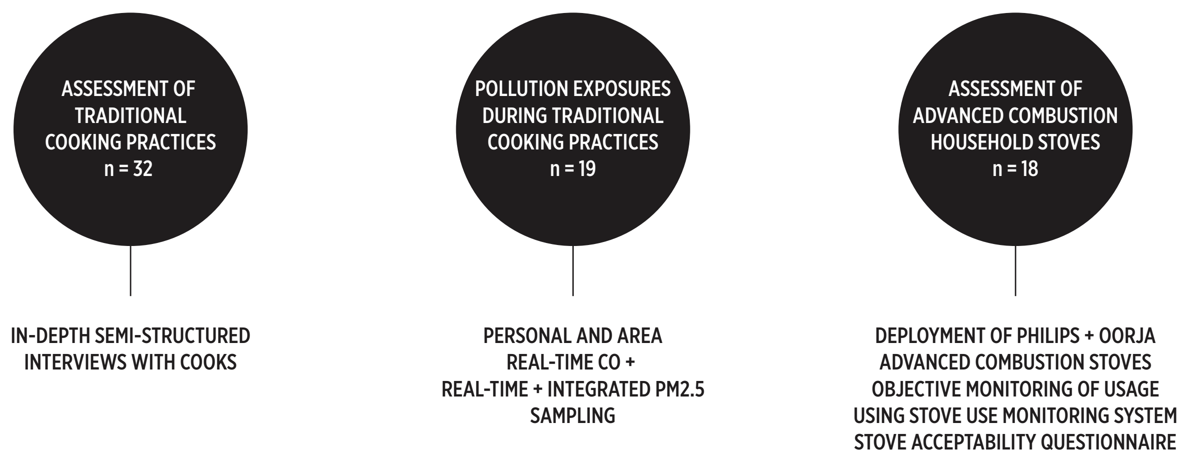


Figure 3.1 Graphical representation of the three primary study components

All interviews were transcribed verbatim. Transcriptions were reviewed against recordings and translated into English. Data were processed through free-listing domain analysis [54,55].

Assessment of pollution exposures during traditional cooking practices
In a separate activity, personal exposures and area concentrations of carbon monoxide (CO) and $PM_{2.5}$ resulting from traditional stove use were assessed in 10 households in two villages by a collaborating team from the Environmental Health Engineering Department at Sri Ramachandra University, Chennai, India. A combination of monitoring durations and techniques was used to determine the feasibility of multiple methods of assessing the primary cook's exposure to combustion-related byproducts. Area sampling of CO and PM occurred continuously for either 24 hours or 48 hours. Personal sampling of PM occurred during cooking periods of approximately 2 hours, during which personal continuous CO sampling also occurred.

Real-time measurements of $PM_{2.5}$ were taken using the UCB Particle and Temperature Sensors (UCB-PATS™, Berkeley Air Monitoring Group, Berkeley, CA, USA). The UCB-PATS is a passive, portable, datalogging optical particle monitor that has been validated in the field in India [5,15]. Data were recorded every minute. Instruments were placed 1.5 meters above the ground in all locations; in the primary cooking location, the monitor was placed 1 meter from the primary stove. UCB-PATS were deployed in one home over three days in the kitchen, primary living area, and outside, in the main household courtyard.

Integrated $PM_{2.5}$ measurements were collected using an SKC Air Sampling Pump (SKC Inc., Eighty Four, PA, USA) at a flow rate of 1.5 liters per minute. $PM_{2.5}$ was collected on 2.0μm pore Teflon™ filters (Pall Corporation, Port Washington, NY, USA), backed with cellulose support pads and placed in a filter cassette connected to a BGI cyclone (BGI Inc, Waltham, MA, USA). Using a laboratory calibrated rotameter, flow rates were measured before and after initiation of the sampling in the field. Separate integrated measurements were collected in the living area for 24 hours (n=4), the kitchen for 24 hours (n=5), and in the vicinity of the primary cook during two cooking events (total duration=125±53 minutes, n=10).

Filters were weighed pre- and post-sampling, using a Mettler balance (Mettler of Toledo, Inc., Toledo, OH, USA) in a temperature- and humidity-controlled room at Sri Ramachandra University. Filters were conditioned for 24 hours prior to weighing.

Real-time CO concentrations were assessed using the Draeger Pac 7000™, a portable, electrochemical CO sensor. The Pac 7000 recorded the CO concentration every minute during the monitoring period. Personal CO was assessed for 24 hours on 9 primary cooks. Correlations between logged data from the Pac 7000 and corresponding integrated $PM_{2.5}$ samples during the same cooking events were investigated.

Exploratory assessment of advanced combustion stoves

In 17 households, two advanced combustion stoves (Figure 3.2), both relying on two-stage combustion with forced air, were assessed. The stoves were chosen based on their availability on the Indian market [56] and their best-in-class laboratory and field-confirmed efficiency and emissions performance [27,57], indicating potential to protect health in homes. Kar et al found that the Philips reduced black carbon emissions in the field by approximately 77% when compared to a traditional, mud cookstove and reduced concentrations in the breathing zone by approximately 70%, though the latter reduction was not statistically significant due to intra-test and device variation. Jetter et al found that a prototype Philips blower stove reduced carbon monoxide and PM emissions in the laboratory by ~90% relative to a traditional three-stone open fire [57].

(A) (B)

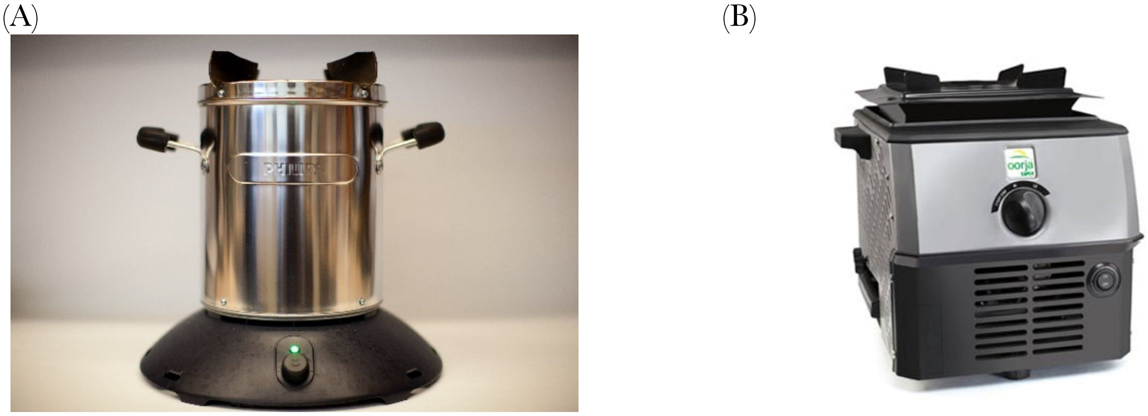


Figure 3.2 Advanced stoves evaluated in Palwal, Haryana
A is the Philips Woodstove Model HD4012. B is the Oorja (photo courtesy First Energy, India). Both are manufactured in India.

The Philips burns biomass and requires minimal fuel processing – fuel must be chopped into pieces less than approximately 2.5 cm in diameter and 5 cm long. The Oorja™ uses manufactured biomass pellets. Both stoves have a controllable electric fan powered by a rechargeable battery and thus require at least intermittent access to power. Manufacturers of both stoves claim that a single charge can provide power to the fan for seven to eight hours of cooking. To the best of our knowledge, there is no peer-reviewed published literature examining the acceptability of either stove amongst rural communities in north India.

Nine households received the Philips and eight received the Oorja in convenience samples of villages. Primary cooks were trained in stove use by field workers. Stoves were given to the households in their original packaging with instruction manuals written in Hindi and English. Philips users were instructed on proper processing of biomass prior to adding it to the combustion chamber. Oorja users received an allotment of fuel pellets and were given contact details for field staff, from whom they could receive additional allotments as needed. The assessment had the following two parts.

Assessment of advanced cookstove usage

Objective usage of stoves was assessed using the Stove Use Monitoring System (SUMS™, University of California, Berkeley). The SUMS [19,20,58] consists of a combination of a small, unobtrusive, battery-powered, temperature data-logger (Maxim Integrated Products, Sunnyvale, CA, USA) and related signal-processing software (University of California, Berkeley). Each SUMS is affixed to a household combustion device and records its temperature profile over time.

Prior to the field work, multiple SUMS were attached to both stove types using heat-resistant tape and sampled every ten seconds during three independent cooking events. Optimal positions were determined by investigating temperature traces and choosing a location on the stove that captured temperature variation but did not exceed 85ºC, the maximum tolerable temperature for the SUMS. Locations were chosen to be minimally obtrusive to the cook.

After determining the optimal sensor location, SUMS were programmed to record temperature readings every ten minutes. Data were downloaded every two weeks across a 12-week period by research staff from INCLEN.

Assessment of advanced cookstove acceptability

After distribution of the advanced stoves, INCLEN research staff collected data on stove acceptability amongst primary cooks using a simple questionnaire. The questionnaire was administered at regular 7-day intervals during the 12-week follow-up period. Final analysis on stove acceptability was carried out at INCLEN. Questions fell into the following broad categories: convenience of use, problems experienced, perceptions, and comparisons with the traditional hearth.

Data analysis

Data were summarized and analyzed using R64 (R version 2.13.2, R Foundation for Statistical Computing, Vienna, Austria) and Microsoft Excel™ (Microsoft, Redmond, WA, USA). Preliminary analyses in Excel included measures of central tendency and event counts. Box plots, confidence intervals, and plots of device signals were created in R64 using built-in packages.

Ethical considerations
The study was approved by INCLEN Independent Ethics Committee (Protocol ID IIEC 002; Ref: IEO-Delhi/Gen Corres 2011/IIEC-19); by University of California, Berkeley Committee for the Protection of Human Subjects (Protocol ID 2010-11-2567); by the Columbia University Human Research Protection Program (Protocol Number IRB-AAAI0866); and by the Indian Health Ministry's Screening Committee (Ref. 5/8/4-1/Env/Indo-foreign/09-NCD-I).

All participants provided informed consent and were given information about the purpose of the study and potential study outcomes. During air pollution monitoring sessions, field staff received permission from participants to place air pollution monitoring devices in their homes. Devices chosen for pollution and stove usage monitoring have minimal risk for participants. Stove training sessions were organized by SOMAARTH technical teams to teach study participants about stove operations and safety protocols and included dissemination of an instruction manual in Hindi. SOMAARTH technicians, during regular field visits, emphasized critical safety measures related to stove usage with study participants and helped troubleshoot any stove problems. Advanced stoves were evaluated based on their safety, reliability, and user-friendliness prior to dissemination.

3.3 Results

Semi-quantitative assessment of traditional cooking patterns
The median age of the 32 primary cooks was 32 years (range 18– 65 years). 59% of participants were illiterate. The average number of household members was 8, but half of the households had less than 6 members. All primary cooks were women; men only cook in unusual circumstances. The majority of households did not purchase their solid cooking fuel and all used wood and/or cow dung for household cooking. Out of 32 households, 20 had LPG stoves in addition to traditional hearths and purchased an LPG cylinder every 1 to 3 months. 28 of 32 primary cooking spaces were located outdoors in a courtyard outside the main house. Courtyards shared many attributes – they were typically large, open spaces bounded on two sides by mud-brick walls. The remaining two sides contained storage and living areas. The courtyard served as a place for household members to congregate and work.

Primary meal preparation occurred twice daily in 27 households. The morning meal was cooked between 5:00 and 9:00 AM; the evening meal was prepared between 5:00 and 9:00 PM. Cooks reported that cooking one meal took, on average, 1.5 hours (range: 0.5 to 2.5 hours). In addition to primary meals, 22 respondents reported primary traditional stove use for tea preparation 1-3 times daily. 10 households reported no further use of the primary traditional stove outside of the two primary meals.

Twenty-five households reported two or more cooking locations. Among the 32 households, fieldworkers identified a total of 68 cooking locations, 71% of which were outdoors and 29% were indoors. Of the outdoor cooking locations, 18% were partially covered, while the others were completely in the open. Of the respondents who had an indoor cooking location, nearly half reported that the indoor space was used only during inclement weather, including rain or extreme heat or cold. Almost all of these cooking locations inside the house had LPG stoves along with traditional mobile hearths.

A total of 90 traditional hearths were identified across the 32 respondent households. Larger households (with a family size of greater than five) had on average 3 hearths, while smaller households (five or fewer family members) had on average 2 hearths.

Two primary types of traditional hearth were identified (Figure 3.3). The stationary hearth, or *chullah* (Figure 3.3A) is made of burnt bricks that are covered on three sides with mud plaster. Fuel is loaded into the front of these devices. 29 of 32 households had *chullah* outside. A portable hearth, or *uthaao chullah* (Figure 3.3B), is also made of brick and mud plaster. These hearths are not fixed to the ground and can be moved indoors during cold or inclement weather. All 32 households used the chullah or uthaao chullah as their primary hearth.

Two additional stove types were identified. The *angithi* (Figure 3.3C) is a top-loading, mobile hearth made entirely with mud. Fuel is loaded into the top of the device. Respondents noted that the *angithi* was used primarily for simmering items for long periods of time − including preparation of animal fodder and heating water or milk. All *angithi* were located outside of the house in a corner of the courtyard. The *haroo* (Figure 3.3D) is a fixed, top-loading, mud and brick hearth. The observed *haroo* were pits lined with bricks and coated with a mud layer. Usage is similar to an *angithi.* 20 households prepared animal fodder daily using either the angithi or the haroo outdoors.

User perceptions: LPG vs traditional hearth

As noted, 20 households had LPG stoves with 2 burners. However, none of the respondent households used LPG exclusively. Most respondents stated that the cost of gas was the major reason for using the traditional stove. Biomass is free and readily available. Almost all stated that chapatis (traditional Indian flat breads) made on the traditional hearth tasted better, remained soft, and spoiled less quickly than those made on the LPG stove. A smaller proportion of respondents indicated that other foods, including deep fried breads and green vegetables, cook and taste better when prepared on a traditional hearth. Finally, respondents stated that milk simmered on a traditional hearth produced more cream.

Respondents stated that while they preferred the traditional hearth, they recognized that LPG cooked food faster, did not produce smoke, was convenient to light and turn off, and allowed use of a pressure cooker.

Respondents ranked fuel efficiency as their primary criterion for a “good” hearth, followed by decreased smoke emission. Others mentioned the taste of the food. Additionally, a small number mentioned design and durability of the stove, convenience of ignition, safety, and mobility as important factors when choosing a hearth.

Figure 3.3 Common traditional stoves found in homes in Palwal District, Haryana
A is the traditional stationary hearth, or chullah. Figure B is the portable hearth, or uthaao chullah, and is used during inclement weather under a covering or indoors. Both A and B are made of mud and plaster. C is a top-loading, fixed hearth made of brick and mud, or haroo. Figure D is a portable top-loading hearth, or angithi. C and D are used for simmering items for long periods of time. D is used during inclement weather under a covering or indoors.

Traditional cooking air pollution assessment

The distribution of gravimetric measurements across locations and monitoring durations is shown in Figure 3.4. Figure 3.5 shows one days worth of real-time PM and real-time CO data. Pollution peaks are consistent with usage peaks (described below). Area measurements in the kitchen and kitchen personal concentrations assessed during cooking events were highest, with respective mean $PM_{2.5}$ concentrations of 468μg/m^3 and 718μg/m^3. Living area concentrations were lowest (315μg/m^3), due in part to the location of kitchens outside of the homes and away from primary living spaces. Outdoor measurements were noticeably elevated, with a mean concentration of 400μg/m^3. Concentrations measured are consistent with other studies across India and other countries in which biomass fuel is burned in traditional hearths [5,33,59]. Daily personal measurements of PM were not possible due to participant refusal to wear sampling pumps with adjoined tubing and cyclones. Although such equipment has been used in other studies in India and elsewhere, our participants stated that the equipment was loud, bulky, conspicuous, and uncomfortable to wear.

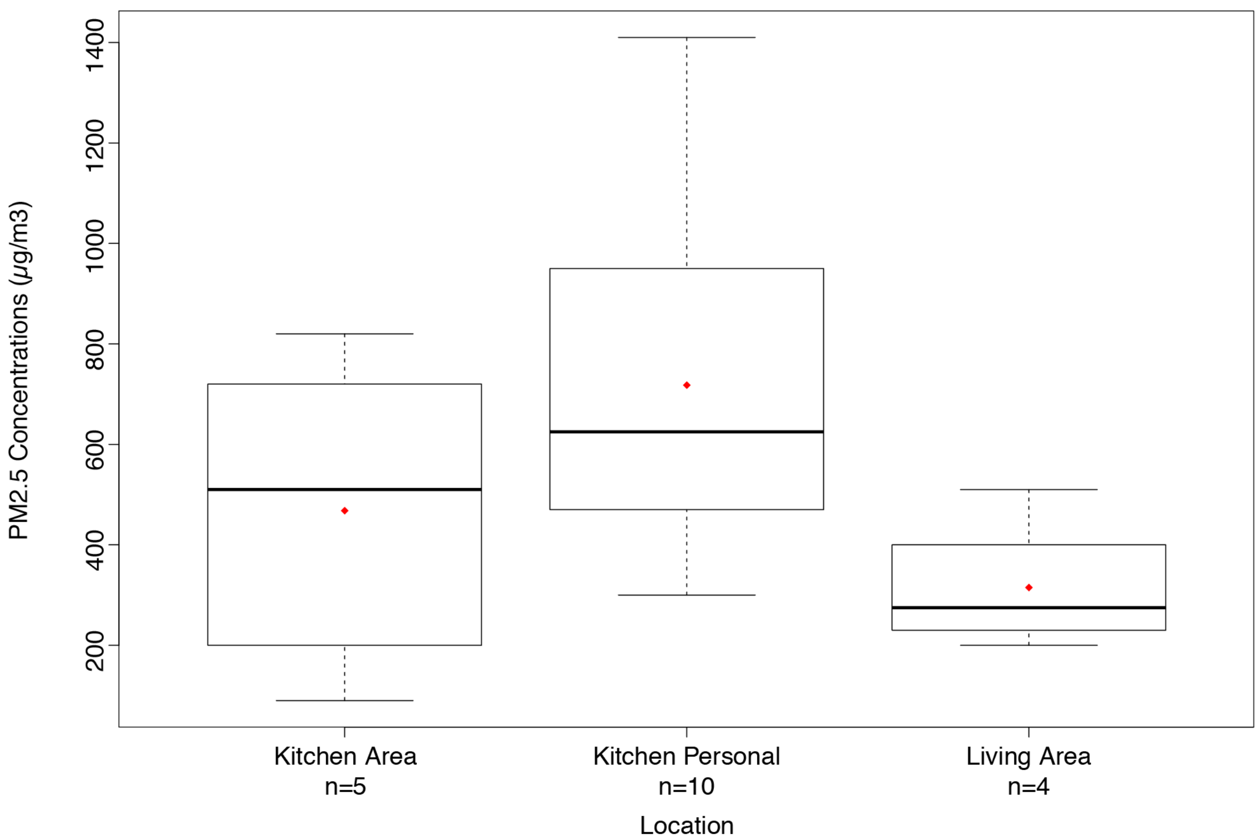


Figure 3.4 $PM_{2.5}$ concentrations across all study households
Each box represents a separate subsample by location and monitoring approach. The height of each box is the interquartile range. The median concentration is marked with a solid black line. The mean concentration is marked by a diamond. The box whiskers extend to 1.5 times the interquartile range. Kitchen Area and Living Area concentrations were measured for at least 1440 minutes; personal concentration measurements were during cooking periods and lasted between 90 and 225 minutes. Outdoor concentrations not depicted due to small sample size (n=3).

The average personal CO exposure (summarized in Table 3.1) during daily cooking was 7.4 ppm, with a range between 0.82 and 18.5 ppm. Non-cooking period concentrations ranged from 0.37 to 5 ppm, with an average of 2.4 ppm. 24-hour personal CO exposures, averaged over both cooking and non-cooking periods, ranged between 0.82 and 5.27 ppm. Concentrations measured were consistent with studies in Guatemala [60-62] and The Gambia [63,64].

(A)

(B)

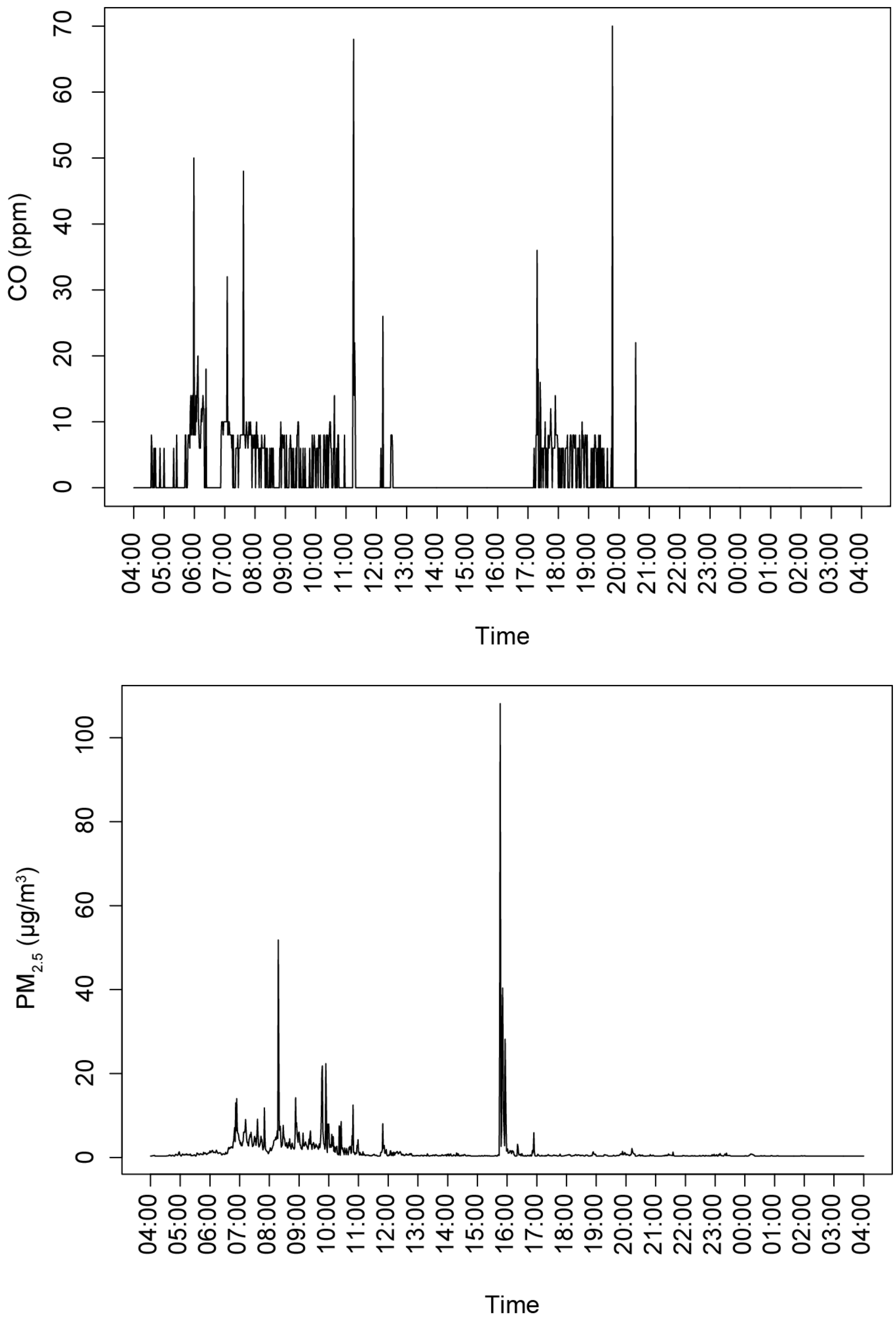


Figure 3.5 Sample plots from pollutant monitors
(A) the Draeger Pac7000 real-time carbon monoxide monitor and (B) the University of California Berkeley Particle and Temperature Sensor (UCB-PATS) logging data during cooking with a traditional stove. Note that peaks roughly correspond with cooking times from Figure 3.6.

Table 3.1 Summary of 24-h pollutant area concentrations
n is the number of samples; SD is the standard deviation of the pooled household concentrations.

	n	Mean ± SD
$PM_{2.5}$ (μg/m^3) Gravimetric	10	718 ± 369
$PM_{2.5}$ (μg/m^3) UCB	7	686 ± 753
CO (ppm) - During Cooking	9	7.46 ± 5.75
CO (ppm) - Non-Cooking	9	2.36 ± 1.43
CO (ppm) - Average	10	2.58 ± 1.52

Pilot assessment of advanced combustion stoves

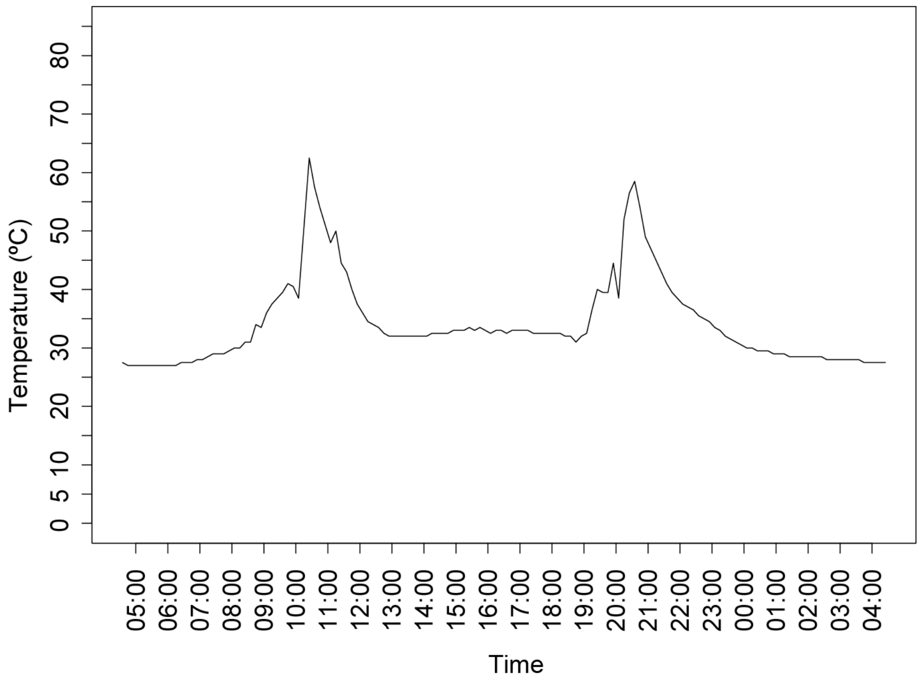
Usage. To determine acceptability of the two advanced stoves amongst primary cooks, we assessed the total time each stove was used and the number of stove events over the 12-week monitoring period. Stove usage data from the SUMS were grouped into three periods (periods 1-3), each consisting of four weeks of data. Counts of usage events were determined using an algorithm[5] and confirmed by manually counting peaks on printed, weekly traces from each household. No significant difference was found between manual counts and the utilized algorithm.

Overall, the Philips stove was used more often and for more hours than the Oorja stove across the entire monitoring period (Table 3.2 and Figure 3.7). Note that both stoves start with high usage, but then diverge, with both stoves being used, though at different levels. For both stoves, the number of events and the total duration of use were highest during period 1 and dropped during period 2. Usage of the Oorja during period 3 was elevated relative to period 2; usage of the Philips dropped during period 3. Even during its periods of lowest use, the Philips was used more than the Oorja. In one household, the Oorja was only used during the preliminary monitoring period; in two other households, the the Oorja was unused during the final monitoring period. The Philips was used consistently by all households.

Acceptability. Findings from the acceptability survey confirm objective usage data. All of the Oorja users reported mechanical or operational issues, including the stove consistently requiring relighting and the fan being "weak." One stove failed completely in the trial. Smoke from the stove was reported as a significant problem by 12.5% of users. At least once during the 12-week follow-up period, 75% of Oorja users stated that the Oorja offered "no convenience". Of those reporting a benefit, 50% reported reduced smoke as the major convenience of the Oorja. 37.5% reported that the portability and speed of cooking were advantageous. When considering the overall utility of the stove, only 12.5% of respondents reported a benefit of the Oorja when compared to their traditional stove.

[5] Algorithm one applied a 6 point moving average to the data. When the temperature increased from point n to point n+5 by greater than 2 degrees, an event was noted as beginning.

(A)



(B)

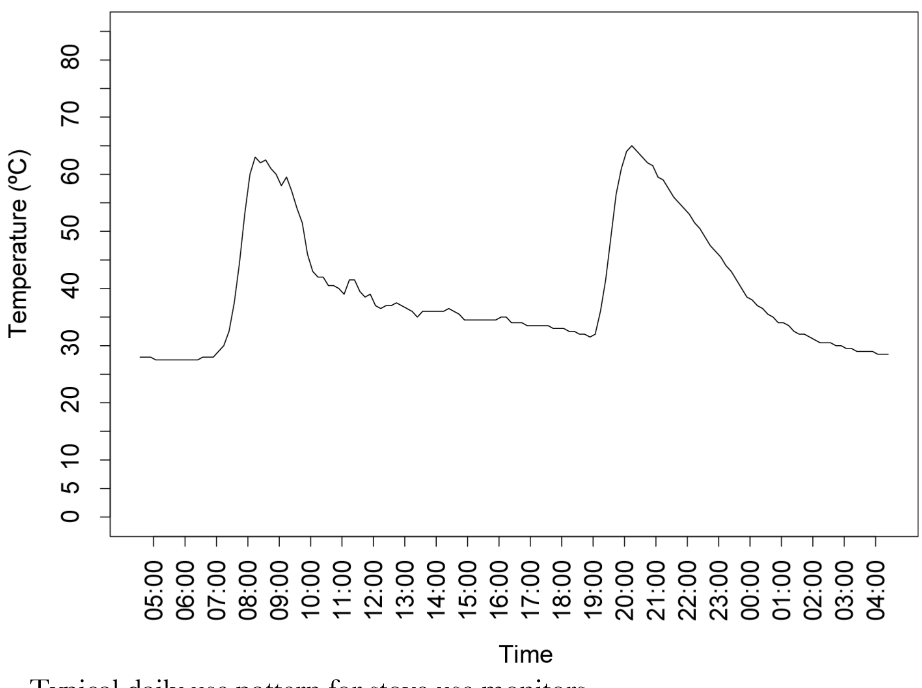


Figure 3.6 Typical daily use pattern for stove use monitors
Philips Stove (A) and the Oorja (B). Peaks in the graphs represent cooking events.

Figures 3.6A and 3.6B display one day's worth of raw data from the SUMS. Elevated temperatures indicate stove usage. A distinct morning and evening stove usage event is visible for each stove type.

Table 3.2 Advanced stove usage over time by four-week periods.
Means with standard deviations of usage per day in hours and events per day are reported for 19 households.

	Period 1		Period 2		Period 3	
	Use/Day (hrs)	Events/Day	Use/Day (hrs)	Events/Day	Use/Day (hrs)	Events/Day
Philips	2.14 ± 0.50	2.13 ± 0.58	1.92 ± 0.84	1.92 ± 0.90	1.84 ± 1.06	1.68 ± 0.99
Oorja	1.24 ± 0.82	0.96 ± 0.61	0.47 ± 0.61	0.56 ± 0.61	0.79 ± 0.90	0.67 ± 0.76

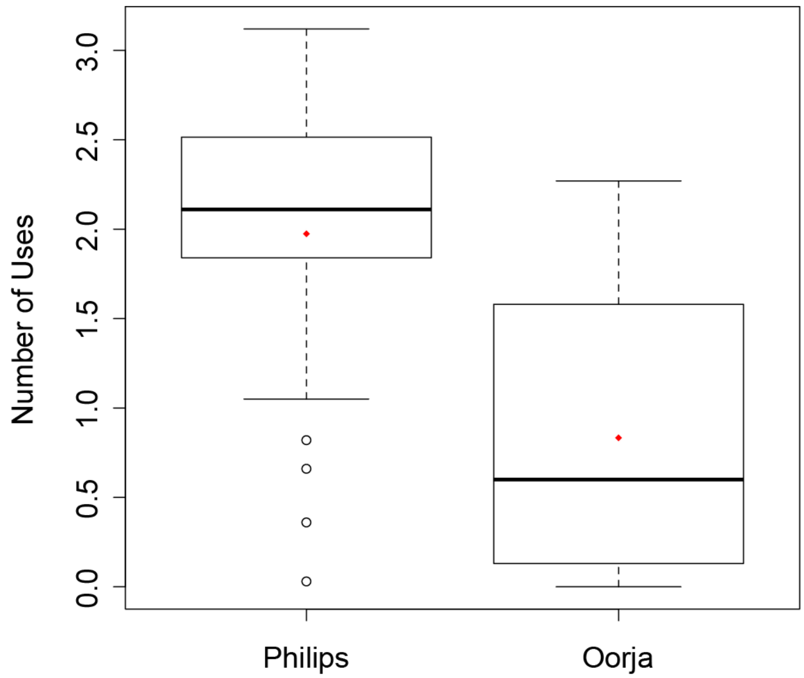
In contrast, consistently throughout the follow-up period, all of the Philips users noted some benefit from their stove. All reported that the stove reduced smoke, increased cooking speed and fuel efficiency, and stated that the stove's portability was a benefit. All reported significant benefits over the traditional cookstove.

For both stoves, 16 out of 17 respondents were of the opinion that the combustion chambers were too small and required constant refueling. They also stated, however, that when functioning properly, both stoves used less fuel than their traditional hearth.

3.4 Discussion

As has been known previously, the concentrations of particulate matter and carbon monoxide measured during traditional cookstove use (both in the cooking area and outdoors) confirm the need for exposure reductions in the household environment. Of the two potential interventions we evaluated, only the forced draft stove using minimally processed biomass (the Philips) was found to be acceptable to participant households in this community. From the outset, the Philips was used more frequently and for more hours per day than the pellet stove, the Oorja. The Oorja users noted the inconvenience of the pelletized fuel and numerous mechanical and operational difficulties. As a result of these findings, we noted that only the Philips was being used during the feasibility study. Although the Philips requires that fuel be broken into small pieces, cooks had no difficulty doing so, because the local fuel consists mainly of cow dung and fine woody debris (twigs). Our results may not generalize to settings where fuels include coarser wood, or where appropriate fuel is scarce. As the Oorja requires a steady supply of pellets, this may reduce its use in poor populations. We understand that stove manufacturers try to improve designs over time, so our conclusions can only refer to the particular models we had available at the time of our study.

(A)



(B)

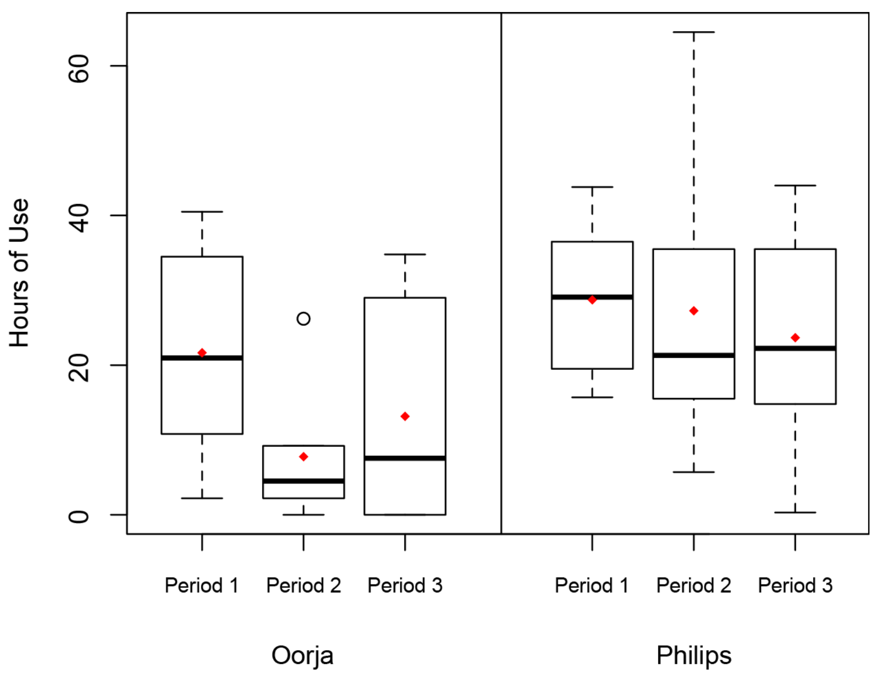


Figure 3.7 Average uses per day and hours of use over time by stove type
(A) shows the average number of uses per day of the Philips Stove vs the Oorja. (B) shows the changes in cumulative hours of use over each period. For both A and B, the length of the box is the interquartile range. The median usage is marked with a solid black line. The mean usage is marked by a diamond. The box whiskers extend to 1.5 times the interquartile range.

This exploratory study − despite relatively small sample sizes in each of its three components − demonstrates that full piloting of advanced cookstoves prior to large disseminations will be necessary to ensure the most appropriate interventions are chosen for each area of use, to take into account local fuel availability and cultural practices. Objective monitoring with the SUMS and assessment of stove performance by questionnaire can help program designers understand why a particular intervention is adopted or abandoned by primary cooks. This is illustrated here in that both stoves perform admirably in the laboratory, but only one was well-received by our community.

Certain tasks − including simmering of milk and preparation of animal fodder − were not accommodated by either advanced stove, but continued to be carried out with one the many traditional stoves employed regularly by households. Future studies should investigate the contribution of these persistent uses of traditional stoves to personal exposures and to ambient outdoor pollution. Exposure reductions due to dissemination of advanced cookstoves may be inconsequential if the household air pollution concentrations remain elevated due to other household combustion sources or external sources of exposure. That cooking tends to takes place simultaneously across households in a community may exacerbate this problem. Work in Mexico has shown that adoption and sustained usage of stoves is a complex, multi-stage process, in which more than one device is routinely used, a practice sometimes called "stacking"[28,29]. Further investigation -- combining qualitative and quantitative data -- of how the advanced stoves integrate into daily routines may help elaborate best practices for exposure reductions and inform future stove designs.

Monitoring of the primary traditional hearth before and after the household receives the advanced stove is one method by which to understand changes in stove use patterns. A challenge moving forward will be what we now realize is a requirement for two related behavioral changes. Users must not only adopt the advanced stove as their primary hearth, but also must decrease (or stop) use of the traditional stoves. Motivating this transition will remain a challenge and may require development of specialized stoves for particular tasks. Our study (described in more detail in Chapter 4) tracked changes in traditional stove use before and after introduction of the advanced stove, allowing better understanding of shifts in usage and how they relate to personal exposures to hazardous air pollutants.

The presence of LPG stoves in many of the households in this study indicates that the traditional stove is preferred over the "ideal" device for some tasks, primarily because of fuel cost, although better taste was also cited as a reason. Further investigation over longer timeframes will be needed to understand how the introduction of an advanced stove alters usage patterns and user perceptions, and in turn how the device is used within the overall household cooking device profile.

Outdoor air pollution levels were higher than expected. Possible explanations for this include (1) preliminary monitoring during the early winter, when inversions are common in northern India; (2) outdoor cooking by many households at the same time, leading to large increases in neighborhood-level pollution; and (3) other sources of ambient pollution, including brick kilns and trash burning. Further ongoing evaluation will better characterize the role of outdoor air pollution in driving daily exposure. High background rates of pollution in this community indicate that achieving significant personal exposure reductions may require interventions focused at the village or regional scale. Targeting individual households may fail to control for exposures resulting from neighborhood traditional stove use.

Understanding exposures in this context, especially amongst the pregnant women we propose to monitor in the larger NBS feasibility study, is challenging. Initial attempts at 24-hour personal monitoring failed due to participant unwillingness to wear larger devices, including pumps, cyclones, and UCBs. Less intrusive or demanding approaches – using a minimally invasive set of equipment, such as the small carbon monoxide sensors, gas diffusion tubes, or prototype personal particulate matter samplers that are now being tested by researchers in the US and Ghana – may offer the best compromise of participant compliance and data quality.

The global resurgence in clean cookstoves projects highlights a need for accurate estimation of personal exposure to validate potential health effects. This study draws attention to the need for further development of valid techniques for investigation of the shifts in household energy usage patterns upon new device introduction. It also highlights the necessity of vetting multiple interventions in small, exploratory studies to find ones best suited to cultural habits and cooking practices.

Chapter 4

Patterns of stove usage after introduction of an advanced cookstove: the long-term application of household sensors

4.1 Introduction

This chapter explores an on-the-ground deployment of an advanced, blower-assisted cookstove in rural India. It evaluated the long-term use of both the intervention and traditional stoves for over one year in an attempt to better characterize and describe usage patterns over time, and demonstrated the viability of using low-cost sensors to track usage for such periods of time. While similar assessments had been performed elsewhere before, to our knowledge at the time of publication, this study was the first to track traditional stoves before and after introduction of an intervention, and offered a new algorithm to convert temperature traces into meaningful metrics, such as number of daily events and daily duration of use in minutes.

Globally, approximately 40% of households rely on solid fuel – including wood, dung, grass, coal, and crop residues – for cooking.[1] The 2010 Comparative Risk Assessment of the Global Burden of Disease attributed 3.6 million deaths yearly to the harmful byproducts of solid fuel combustion for cooking and an additional 0.3 million deaths from contributions of household air pollution to ambient air quality.[2,3] While the proportion of households using solid fuels appears to be declining, the absolute number using these fuels remains fairly constant.[1]

Most efforts to mitigate this health burden have focused on providing biomass-burning stoves that vent pollution outdoors and/or improve combustion efficiency to reduce emission rates. Increasingly, some are focused on providing access to clean energy for cooking – including electricity or liquefied petroleum gas. Several conditions must be met if household energy interventions are to improve health: continuous access to a low-emissions energy source for cooking[2], sustained usage of this energy source, and discarding of the more polluting traditional stoves. Mixed use of clean and traditional stoves – dubbed stove 'stacking' – can mask or negate any potential benefit of an intervention. Stacking is well-documented through surveys [28,29,65,66], though little objective continuous monitoring of usage of multiple cooking appliances during intervention studies has occurred to date.

In Palwal District, Haryana, we provided a fan-assisted, advanced cookstove, with modifications to improve combustion efficiency (not just improve fuel efficiency or vent pollutants outdoors), to pregnant women via local antenatal healthcare system workers. Preliminary research evaluating potential interventions and describing this community has been published[67] and was described in detail in Chapter 3. During that initial work, we identified the stove selected for this study – the Philips HD4012 – as suitable, despite requiring access to power for battery charging and the need to chop the biomass fuel into small pieces. Among other goals, the study evaluated the use of the intervention and primary traditional stoves over time and investigated predictors of usage.

Monitoring usage and adoption of intervention stoves traditionally relied on simple metrics obtained through interviews or by a trained observer. Such practices introduce the potential for bias – due either to recall bias or to changes in behavior due to participants knowing that they are being observed in the study (the 'Hawthorne effect'). Recent work in Rwanda, for example, highlighted that usage estimates obtained from surveys were biased upward relative to objective measures from electronic sensors.[23,68] These biases have been well described in water and sanitation studies, including recent evidence showing significant effects of structured observation on behavior[69] and attempts to address these issues using simple data-logging sensors.[22] Previous studies[19,20,28,58,67] of household energy identified Maxim IC's iButton technology as an objective, field-validated Stove Use Monitor (SUM). iButtons are small, coin-shaped thermometers that log time-resolved instantaneous temperatures at the surface upon which they are mounted. Properly placed, iButtons offer both an objective measure of stove usage and a relatively unobtrusive way to monitor interventions over time. Specific sensor characteristics are described elsewhere.[20,67]

This paper describes time-trends in usage of the intervention and primary traditional stoves in rural Indian homes. We examine how well short-term measures (1, 2, and 7 day mean measurements) of stove use predict study means, with the goal of optimizing sampling times and strategies for monitoring household energy interventions. We believe the dataset described in this paper is the longest and deepest dataset of measured stove usage generated to date, spanning over 15 months of monitoring at 10-minute intervals on both intervention and primary traditional stoves in 200 homes (~21 million datapoints). Measuring multiple stoves required creation of new metrics to characterize shifts in usage patterns over time. Our secondary focus – on reducing total monitoring duration for assessing use, without compromising data quality – informs strategies to optimize the conflicting goals of precise measurements and efficient fieldwork.

4.2 Methods

Study site

This study took place approximately 80 kilometers south of New Delhi at the International Clinical Epidemiology Network (INCLEN) SOMAARTH demographic, development, and environmental surveillance site[67] in Palwal District, Haryana, India beginning in November of 2011 and ending in March of 2013. At the time of the study, INCLEN was carrying out

Figure 4.1 Traditional and intervention stoves and placement of stove use monitors
A is a typical traditional wood and dung-fueled stove. The inset image shows the Stove Use Monitor and its holder. B is the Philips intervention stove. A metal sheet stamped with a unique identifier and machined with a hole was used to securely hold each stove use monitor.

demographic and environmental surveillance in 51 villages, covering a population of approximately 200,000.

During the study, ambient temperatures varied widely by season, reaching a maximum of 45ºC in May and a minimum of 4 ºC in January (Appendix Figure C1). Temperature data were logged every minute by the project meteorological station (Onset Microstation, Onset Computer Corporation) at the INCLEN field headquarters in Palwal town, between 5 and 12 kilometers from study villages.

Study sample

The current study focused on 7 rural villages, selected based on their use of biomass for cooking, total population, and their accessibility to the SOMAARTH field headquarters. 205 pregnant women were recruited from these villages. All households recruited into the study used dung, wood, and crop residues in a traditional hearth (Figure 4.1A) as the primary means of cooking. Nearly all homes (n=200) cooked outdoors.

Intervention

The Philips HD4012 (Figure 4.1B) is a top-loading, fan-assisted semi-gasifier stove fueled by small wood pieces 5 cm in length and up to 2.5 cm in diameter. It contains a rechargeable battery that powers a fan used to enhance combustion efficiency. The fan is adjustable via a knob on the front of the stove. The HD4012 requires access to electricity for intermittent charging. Initial selection of the Philips stove was based on its performance in laboratory testing by the US EPA, which found it to be amongst the cleanest stoves evaluated using standard simulated cooking methods.[9] Field emissions from this stove were evaluated by other research projects in India[27,70] and our research team validated this stove's acceptability in the community prior to this project.[67] At the time of the study, the stove was produced in Ghaziabad, India, and sold for approximately 60 USD.

Participants who received the Philips stove were trained on proper stove use and maintenance by community health workers and INCLEN field staff. Contact information for INCLEN's field office, which was equipped with spare Philips parts and had access to trained technicians and electricians, was provided to participants in case of any stove malfunction, error, or other user complaint. Complaints could be filed during regular household visits by INCLEN field staff, through calls to INCLEN, or by visiting the field headquarters. Upon receipt of a complaint, repair attempts were undertaken first by INCLEN support staff and then, if necessary, by electricians. A supply of replacement stoves was available to avoid prolonged interruption in homes with stove failures. Detailed logs of stove reliability, malfunction, and maintenance were maintained by INCLEN field staff (see Appendix C).

Stove Use Monitoring

Upon enrollment into the study, field staff obtained informed consent, administered a baseline questionnaire, and installed a SUM on the primary traditional stove in each participant's household. The primary cook was informed of the purpose of the sensor. SUMs were placed in a custom-made metal holder and plastered onto the traditional stove side-wall with the same slurry of mud and water used to construct and repair stoves. The holder and a SUM can be seen in the inset image in Figure 4.1A. The selected SUMs placement location did not disturb standard cooking practices, was protected from overflows and spills, and captured variability in temperatures adequately. Stoves varied in shape and size between households; SUMs were placed in approximately the same location on each stove throughout the study.

Within four weeks after pre-intervention monitoring began, the Philips intervention stove, pre-fitted with a SUM (visible in Figure 4.1B), was delivered to the home. A custom-made metal bracket, stamped with a unique stove ID, was used to hold the SUMs in an identical location on all intervention stoves.

SUMs logged instantaneous temperature every 10 minutes continuously throughout the study. Field workers visited homes every two weeks to inspect stoves and download data from the SUMs. SUMs were reprogrammed after each download. Raw sensor data were acquired using a Touch and Hold Probe connected to a USB to 1-Wire RJ11 adaptor (Maxim Integrated, San Jose, CA, USA). Data transfer took approximately 2-5 minutes per stove and involved holding the probe to the surface of the iButton. Stove usage files were transferred to the field office, where they were inspected for errors and minimally processed.[71] Filenames contained metadata, including stove type (Philips or traditional), household ID, and download date. Raw files were archived at the field site and at INCLEN headquarters in New Delhi. Cleaned files were transferred to a secure server in the School of Public Health at the University of California, Berkeley, and analyzed using R. Approximately 20.6 million SUMs data points were collected during the main study, representing 143,000 stove-days of data from 408 stoves.

Data processing

The number and duration of usage events, derived from raw SUMs temperature traces, were determined for each stove on each monitored day. Algorithms for processing SUMs data were created using an iterative process, beginning with recommendations from the literature that identify events by setting thresholds for the rate of increase and decrease in temperature. [20] Due to the high variability in ambient temperatures in Palwal, existing algorithms were altered to better suit the local climate and stove types. We took advantage of our continuous ambient temperature measurement to ‘correct’ for diurnal variation. To compensate for variability in temperatures between households and the field office, we calculated the mean and standard deviation of ambient temperature for each recorded hour during the study. These values were used to create thresholds for evaluating whether a stove was in use or not.

For each stove, the daily recorded SUMs temperature range (D_{range}) was calculated by subtracting the daily minimum temperature from the daily maximum temperature. SUMs data were then merged with data for mean hourly ambient temperatures ($H_{mean\ amb}$) and their standard deviations ($H_{sd\ amb}$). A stove was considered in use when the SUMs temperature exceeded the mean ambient temperature plus 6 times its standard deviation. Any period detected for which D_{range} was less than 20 ºC was marked as a period of non-use. To count the total number of daily uses, periods of use that occurred less than 40 minutes apart were treated as a single use. This clustering threshold was based on manual observation of temperature traces. For each stove, durations of daily use and number of uses per day were saved.

Analyses and interpretation of sensor data

Summarized data were analyzed to understand trends in usage of both the traditional and intervention stoves. All analyses were restricted to households for which we had at least 2 days of pre-intervention data (n=177). Analyses were performed separately (1) for the entire data set for these households and (2) for days on which data were successfully collected from both traditional and intervention stoves (see Appendix C).

The proportion of stove use-time spent using the Philips intervention stove was defined as

$$Proportion_{Philips} = \frac{Duration_{Philips}}{Duration_{Philips} + Duration_{Traditional}}$$

All durations were calculated in minutes. While the proportion of time spent using an intervention is useful to track adoption, it does not take into account gains in efficiency of heat transferred to the pot by the intervention stove, leading to shorter cooking times, and therefore does not allow direct comparison between stoves. Thus, we linked durations of cooking derived from the SUMs with cooking power from laboratory studies[9] to determine the utilized cooking energy (UCE) in megajoules (MJ):

$$\frac{MJ\ Cooking\ Power_{stovetype}}{min}\ x\ Mins\ Use_{stovetype} = Utilized\ Cooking\ Energy_{stovetype}$$

Calculation of UCE allowed estimation of changes in total energy used before and after deployment of the intervention. Laboratory cooking power estimates were derived from controlled burning for water boiling using uniform wood fuel and may not be representative of conditions in the field, where multiple biomass fuels of varying moisture contents may be used.

Statistical tests and modeling

The metrics described above were used to create a log of daily household usage, including the number of uses, duration of use, and estimated energy used by each stove. Overall trends in use of the traditional stove before and after introduction of the intervention were compared using t-tests.

We evaluated the change in daily mean traditional stove use after introduction of the intervention using linear mixed models to partition the between- and within-household variance components and to calculate the intraclass correlation coefficient (ICC, the proportion of variability explained by between subject differences). Models took the following form

$$Y_{ij} = \beta_0 + b_i + e_{ij}$$

Where Y_{ij} is the i^{th} duration of use in household j, B_0 is the overall intercept, b_i is the random effect for household *i*, and e_{ij} is the leftover error. This baseline model was run first for the combined dataset and then separately by period (pre-intervention and post intervention) for the traditional stoves. Variability in Philips usage was assessed independently in the same fashion.

Sampling strategies

We additionally evaluated how well short measures of usage predicted the study average during stable periods of usage. This analysis was restricted to the traditional stove, which exhibited stable use patterns, and was performed independently for the pre- and post-intervention periods. We calculated means from varying time periods (one day, two consecutive days, two random days, one week, and one day per month) of usage data selected randomly from each household and study period and compared it to the mean duration of use for the entire study period. For shorter measures, we calculated the probability of a random measurement falling within a precision interval (for instance, within 20% in either direction of the period mean).

4.3 Results

Pre- and post-intervention stove usage

During the pre-intervention period, usage of the traditional stove was measured in 177 homes for, on average, 34 days (SD = 35, range = 3 – 103). In this period, households used their primary traditional stove 1.4 times (SD = 0.8), for an average of 209 minutes (SD = 105) per day. After introduction of the intervention, the traditional stove was monitored for, on average, 251 days (SD = 97, range = 52 – 426); the Philips stove was monitored for, on average, 358 days (SD = 54, range = 139 – 433). During the post-intervention period, households exhibited a significant mean decrease in the use of their primary traditional stove to 144 minutes per day ($p < 2.2e\text{-}16$, SD = 134) once daily. The intervention stove was used, on average, 0.6 times daily (SD = 0.8) for 60 minutes (SD = 87) after its introduction.

A small number of characteristic stove adoption patterns was observed across households. Figure 4.2 shows the two most common patterns of the transition between traditional stoves and the intervention stove, as illustrated by data from two study households. In both panels, the dotted blue line is the SUMs trace from the traditional stove; the solid red line is the trace from the Philips. Pre- and post-intervention patterns of use are shown. In the upper panel (“Mixed Use”), the Philips is used upon introduction repeatedly over the course of a week, concurrently with traditional stove use. Philips use declines and tapers off in later weeks. In the lower panel (“Philips Use”), use of the traditional stove halts after Philips introduction. A third pattern, in which the Philips was rarely or never used, was observed but is not displayed. These patterns were typical of the larger population during the first month after introduction of the stove.

Post-intervention cooking patterns

Use patterns during the first through third months post-intervention in homes with SUMs data available on both stoves for at least 15 days per month are described in Table 4.1. During the first month with the Philips, almost all homes used both stoves (n=152). 6% of homes used the Philips exclusively (n=9); only one home did not use the Philips. Among the homes using both stoves, the Philips accounted for greater than 80% of cooking events in 17% of homes (n = 28).

Subsequent months exhibited wide variability between and within homes (Appendix C). Among the 9 homes that exclusively used the Philips during the first month, average use of the Philips decreased from 111 minutes daily during the first month post-intervention to 78 minutes daily across the remaining months. Traditional stove use increased from 0 to 52 minutes daily across the same period. Additionally, all households exhibited multiple days during later months in which neither stove was in use, suggesting that food was obtained by other means (from relatives or purchased), cooked in alternate locations, or cooked using stoves not fitted with SUMs. Similar trends were noted for homes exclusively using the Philips in months two and three.

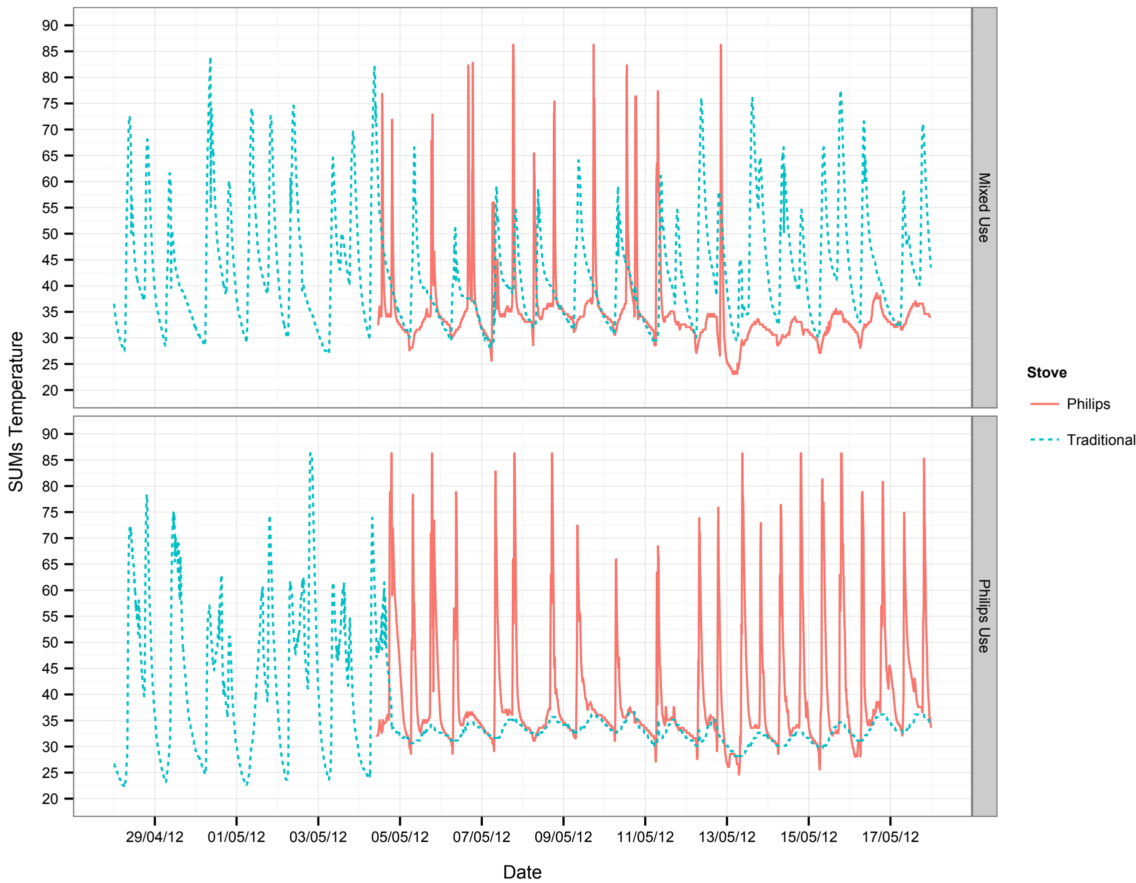


Figure 4.2 SUMs data from households with different usage patterns
Panels show temperature traces for the traditional stove (dashed blue) and for the Philips stove (solid red).

Table 4.1 Distribution of cooking events using Philips stove

Days After Intervention	N	Percent of Total Cooking Events using Philips n (%)							
		No Use [a]	0	1-19%	20-39%	40-59%	60-79%	80-99%	100%
0 – 30	162	0 (0)	1 (0)	11 (7)	34 (21)	55 (34)	33 (20)	19 (12)	9 (6)
31 – 60	155	5 (3)	8 (5)	25 (16)	25 (16)	34 (22)	23 (15)	13 (8)	22 (14)
61 – 90	146	4 (3)	8 (6)	30 (20)	29 (20)	19 (13)	13 (9)	16 (11)	27 (18)

[a] No use of either stove recorded

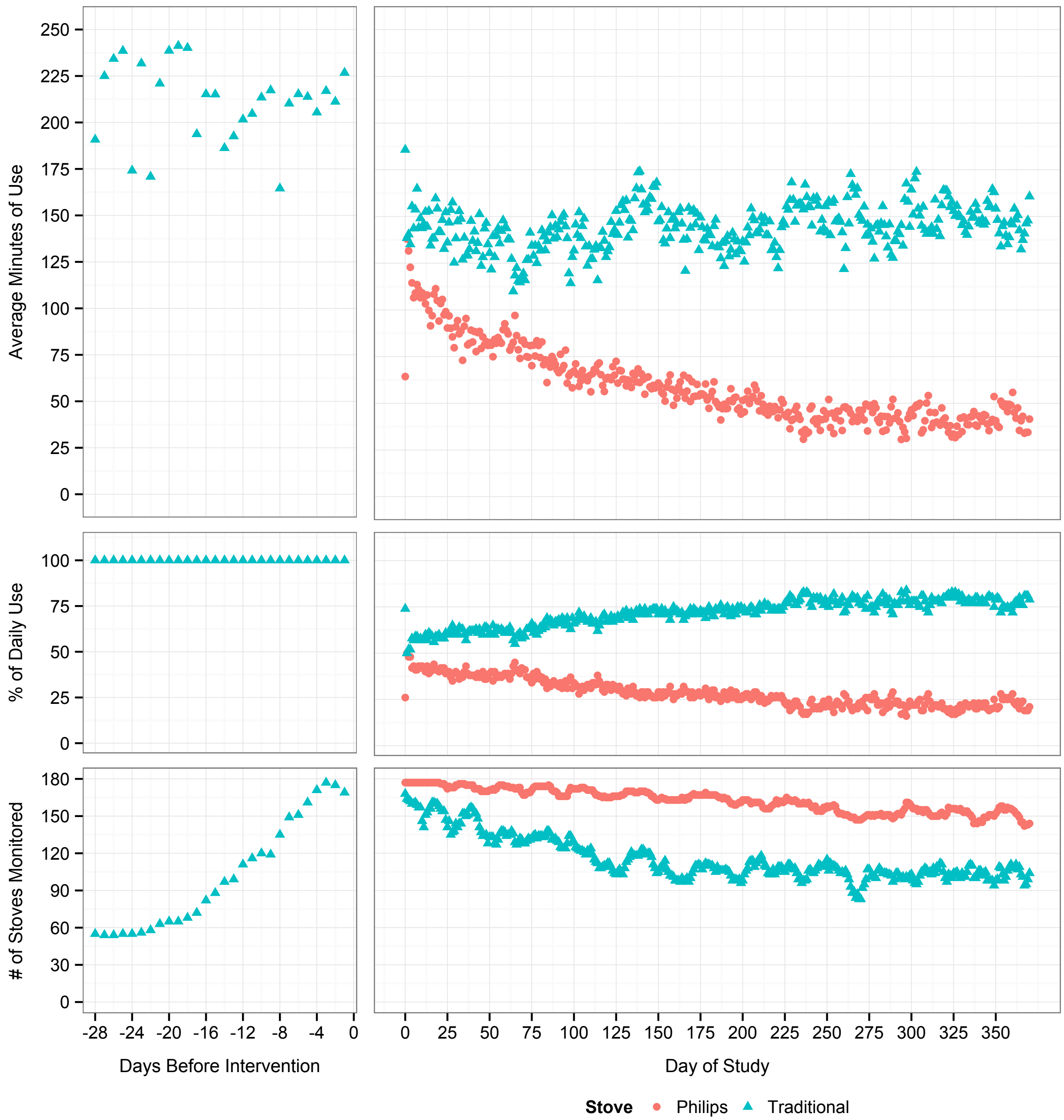


Figure 4.3 Use and monitoring of traditional and intervention stoves throughout study
The upper panel depicts daily mean usage of monitored stoves by stove type. Day 0 is the day the intervention stove was introduced. The middle panel depicts the percent of cooking time each stove was used. The bottom panel depicts the number of stoves monitored per study day.

The variability in usage of the intervention and the lack of displacement of cooking tasks from the traditional stove to the intervention is emphasized at the study population scale in Figure 4.3. Between introduction of the intervention and post-intervention day 200, there is a significant and consistent decrease of 0.28 minutes/day in use of the Philips ($p < 2e-16$); between day 200 and the end of monitoring, usage stabilizes but continues to decrease by 0.04 minutes per day. The traditional stove use after Philips introduction was stable. Similar trends were noted for daily use event counts over time (see Appendix C).

Most of the total variability in usage across stove types was due to variability within homes – 66% across periods for traditional stoves and 78% for intervention stoves. The total variability was highest for traditional stoves in the post-intervention period, perhaps indicative of either a shift first to and then from the Philips or mixed use of both stoves. Appendix Table C3 shows the means of use duration overall and by stove type and period and presents the calculated ICCs, the proportion of variability explained by differences between subjects.

Utilized cooking energy

Prior to the intervention, households utilized 15.5 MJ of energy per day (SD = 1.5) from cooking with their traditional stoves (Figure 4.4). After introduction of the intervention stove, utilized cooking energy from the monitored traditional stove decreased significantly to 10.6 MJ per day (SD = 0.86, $p < 2.2e-16$). In the first month after introducing the intervention, however, total average utilized energy increased to 21 MJ daily, due to use of both stoves. Counterintuitively, perhaps, decreasing usage of the more efficient Philips in subsequent weeks led to decreasing total energy use. Assuming the rate of energy consumption of each stove remained constant throughout the study, the average daily utilized energy across the post-intervention period increased to 16.3 MJ ($p = 0.003$).

Comparing short-term measures of stove usage to study means

We evaluated the ability of “short measurements” of cooking duration –1 day, 1 day per study month, 2 random or 2 consecutive days, and one consecutive week – to predict mean stove usage of the traditional stove during the pre- and post-intervention periods. These periods for the traditional stove were selected because they exhibited relative stability over time, as compared to the Philips.

Short measurements had a low probability of predicting the study-wide mean of stove usage. Precision varied across the pre- and post-intervention periods (Appendix Figure C5 and Table C4). Short-term measures adequately predicted pre-intervention means with traditional stoves. During this period, a consecutive week of sampling had the highest probability (75%) of being within 20% of the long-term mean. After introduction of the intervention stove, short-term means performed poorly. Just 18% of random single days were within 20% of the long-term mean for the traditional stove. The mean of samples taken for one day per month post-intervention had a 66% chance of being within 20% of the long-term average.

4.4 Discussion

We report on the usage of an intervention stove distributed to 177 pregnant woman and related changes in use of the traditional stove over approximately 60 weeks in rural India. The dataset consists of one of the largest and longest objective measurement campaigns of stove usage to date. By deploying stove use sensors for over a year, we were able to track and report for the first time the changes in usage of an advanced cookstove intervention and the primary traditional stove over time.

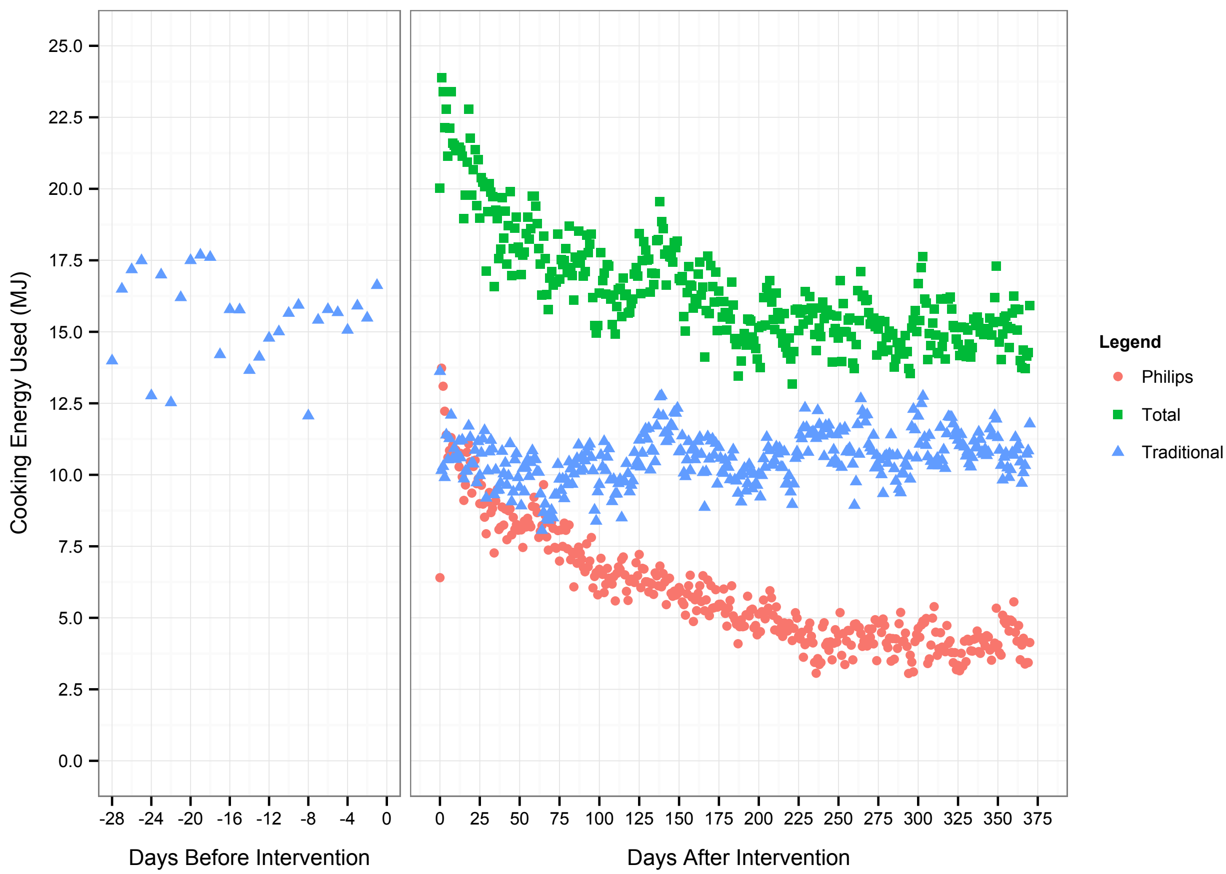


Figure 4.4 Utilized cooking energy in megajoules throughout intervention
The utilized cooking energy is presented separately for the traditional and intervention stoves (blue and red, respectively) and pre and post-intervention periods. The total energy use is presented in green.

Analysis and application of stove usage data
Few algorithms for converting temperature traces to event counts and durations of use have been published. We offer a novel analysis method: usage events defined as periods that deviate from ambient temperatures. This method does not rely on any additional assumptions about the distribution of the data and facilitates relatively fast analysis of large volumes of data. It does, however, require local measurement of ambient temperature, which can introduce additional cost. We focus on durations of use, as we believe this to be a more health-relevant metric and a

better indicator of potential risk than number of events, which can easily be obtained from duration data if needed (see Appendix C).

Further evaluation of this algorithm is ongoing on both previously collected and new SUMs datasets. We are additionally investigating the feasibility of household or village level "ambient SUMs" to aid with signal processing and to account for microclimatic variability not captured by a single, meteorological station. Finally, we are monitoring usage on many different stove phenotypes globally; these activities will help optimize SUMs placement practices, and evaluate and hone the described algorithm to determine its broader applicability.

We see a need for standard methodologies for interpretation of iButton signals that cater to specific research or programmatic goals. Daily time of use and number of uses are simple metrics obtainable from SUMs data through a number of methods. Inter-study comparisons of usage may be complicated, however, by variation in the algorithms used to generate these metrics. For instance, estimated time-of-use is impacted by the threshold at which the stove is no longer considered to be on; the estimated number of uses is similarly affected by decisions about clustering of temperature peaks. Clear specification of algorithm parameters – ideally in the form of open-source code – and evaluation of algorithms in multiple studies can help clarify differences between results obtained using different methods.

Stove usage and adoption in Haryana

We found linearly decreasing population-scale trends in usage of the intervention stove over time. This trend leveled off between 175 and 200 days post-intervention. While usage of the intervention had not completely ceased at the end of data collection, the number of homes using the intervention stove regularly and the related durations of use were lower than immediately after stove distribution. Our findings are supported by other studies which have (1) indicated "stacking" of devices throughout the adoption process[58] and (2) acknowledged a trial period during which the household evaluates the suitability of the intervention. [28,29]

Utilized cooking energy showed similar trends, with an increase in total UCE following introduction of the Philips, followed by a leveling off and stabilization. Future studies should focus on similar calculations to understand if there is a 'rebound effect', as discussed elsewhere[72] in the household appliance literature. In our setting, addition of the advanced stove seemed to increase overall energy use, perhaps because the users took advantage of an additional stove to provide more cooking services, rather than substituting the Philips for the traditional stove. Any future studies seeking to calculate UCE should evaluate cooking power in the field, as laboratory and field stove performance parameters often vary widely[73-75]. Because we relied on these laboratory estimates and applied them uniformly over the study period, we may be mis-estimating the actual utilized cooking energy.

Our findings indicate that the Philips may have temporarily offset a portion of measured traditional cookstove usage, albeit in a way that may have increased total energy use. Despite this continued use of the Philips, however, it failed to become the dominant stove used in the home, as would be necessary to maximize health protection. Changes in exposure during the current study will be reported separately.

Importantly, without measurement of usage of both the primary traditional and intervention stoves, we would have been unable to make any determinations about the role of the Philips – as an added cooking appliance – in household cooking. Finally, we would not have observed the initial uptick and subsequent decrease in UCE after introduction of the intervention.

Stove usage variability

The high within-household variability of daily usage of both stoves – especially in the post-intervention period – indicates that care must be taken when using short-term measures of usage to predict long-term means. Specifically, after deployment of an intervention, a period allowing households to reach an equilibrium is recommended to prevent mis-estimation of long-term trends. This stands in stark contrast to previous work in Guatemala [58], where the majority of variability was found to be between households. Most likely, this is due to the difference between the character of the intervention in Guatemala, which was well known to the community, locally created, and fixed in place, and the intervention in India, which while vetted in the community was a portable, engineered object brought in from elsewhere.

Continuous measurements allowed us to evaluate the ability of short-term measurements to predict the long-term mean. Short-term measurements of one or two consecutive days did a poor job of predicting the long-term mean, with the majority of measurements deviating from the mean by over 20%. Measurements that were spread through time – for instance, one 24hr measurement per month of the study – were much closer to the long-term mean. These findings suggest that future intervention studies should measure stove usage regularly to capture inherent variability in household behavioral patterns and to best capture changes in usage over time. Given that short-term measures fail to accurately predict long-term means in relatively stable situations, their value in dynamic situations, such as the days and weeks following intervention introduction, is extremely limited. Attempts to assess "adoption" and use must track behaviors consistently for longer periods of time.

Limitations and challenges

This study has a number of limitations. Stoves were given to participants free-of-charge, which has been shown to impact perceptions of value [24]. Participants were enrolled based on pregnancy during the initial phases of the study and may not represent the broader population. Cultural cooking practices related to pregnancy may impact adoption of an intervention stove; initial and long-term usage in households without a pregnant woman may be more consistent or significantly different from the patterns we observed. However, as our study population represents a particularly vulnerable group, indications on how they use this free intervention can inform future studies targeted towards similar communities. Second, we were unprepared to instrument the variety of other traditional stove types found in many households. While we placed two sensors, one on the intervention stove and one on the participant-reported primary traditional cookstove, it is possible that other traditional stoves were also used during the study period. Further, there is possibility of the Hawthorne effect: instrumentation of the primary traditional cookstove may have shifted usage to other, unmonitored traditional stoves. Among users who exclusively used the Philips during month 1 or 2 of the study, we noted multi-day periods of inactivity with both monitored stoves in subsequent months, indicative of cooking elsewhere or use of another stove. We believe either of these reasons may account for the, on average, lower levels of traditional stove usage in months 1 and 2 than during the pre-intervention period. As a result of these caveats, our study paints only a partial picture of the true usage patterns in the home. As these secondary and tertiary stoves were reported to be used only for simmering milk or cooking during inclement weather, we do not believe there were wide changes in their use as a result of introduction of the Philips. We cannot, however, discount the possibility of use of unobserved and unmonitored stoves. Finally, the high number of interventions that suffered one or more mechanical failures calls into question the reliability of this intervention without significant infrastructure and spare parts to facilitate repair.

A number of challenges arose during the study. The fieldworker burden for this study was high, with a small team of fieldworkers visiting each household every two weeks. Households were spread over a relatively wide area, leading to significant transit time and costs and fieldworker turnover. Similarly, the volume of data proved to be a logistical challenge to manage, clean, and transfer. Strict protocols and fieldworker assurances facilitated analyses but could not, inherently, decrease data transfer and processing times. SUMs on traditional stoves were especially difficult to maintain over long periods of time due to challenges with placement related to overheating and exposure to water (see Appendix C). We are exploring alternate measurement techniques – including infrared thermometers, thermocouple-based data-loggers, and wireless transmission of data – to improve data completeness and fidelity for traditional stoves. Comparisons of data measured with SUMs to participant-reported stove use and perceptions of the Philips as a replacement for the traditional stove are in preparation. Such comparisons have, in some cases [58], revealed that reported stove use is similar to measured use, while in other cases reported use exceeds measured use[23]. Future intervention studies should focus on long-term objective measurement of stove use and, using qualitative methods from behavioral science, seek a deeper understanding of the individual and community behaviors motivating use or non-use of an intervention.

4.5 Conclusion

As noted elsewhere[28,75], stove usage is a critical link between the potential and delivered benefits of intervention programs. Monitoring of usage over time is necessary to fully understand the potential for delivery of those benefits; in this study, short-term measurements of benefits immediately after intervention distribution would have been misleading and potentially led to mistaken claims of benefits.

The low long-term usage of the intervention stove, while disappointing, is informative. It indicates (1) that preliminary work, while valuable to assess initial feasibility of an intervention, will most likely not predict long-term viability; (2) that measurement of usage of both traditional and intervention stoves is required – over time – to fully understand and accurately characterize adoption of an intervention and changes in traditional habits; and (3) that a combination of more transformative, aspirational, and reliable interventions – that can fully displace the traditional stove – and education and training, to sway participants away from the old stove – will be required to fully realize benefits.

Chapter 5
HAPIT, the Household Air Pollution Intervention Tool, to evaluate the health benefits and cost-effectiveness of clean cooking interventions

5.1 Introduction

Globally, approximately 40% of the world's population relies on solid fuel combustion for cooking [1]. The household air pollution (HAP) resulting from the use of these fuels (including wood, dung, coal, and crop residues) results in approximately 4 million premature deaths yearly [2,36] and 108 million lost disability-adjusted life years (DALYs) in low and medium income countries (LMICs). This comes from HAP's impact on a range of diseases, including chronic obstructive pulmonary disease (COPD), ischemic heart disease (IHD), stroke, and lung cancer (LC) in adults and acute lower respiratory infection (ALRI) in children. Recently, in response to this large health burden, international organizations and governments –spearheaded in part by the Global Alliance for Clean Cookstoves – have focused on efforts to provide reliable clean cooking technologies to solid fuel users. Deployed interventions span a range of technologies, including simple "improved" chimney stoves [4,42], 'rocket' stoves [11], advanced cookstoves with fan-assisted combustion [10,43], as well as clean fuel (including LPG, natural gas, biogas, ethanol and electricity) interventions [47,76].

Selecting an intervention requires balancing a number of competing priorities, including the cost of the intervention; its effectiveness, as proven in the lab and pilot field studies; its cultural acceptability and ability to meet local cooking needs, and its inherent requirements, like the need for fuel processing, the intervention's durability, and power constraints. One way to frame these characteristics is at the scale of a large, national program, with consideration of its potential to improve quality of life and avoid ill-health, expressed in terms of dollars spent on its deployment and evaluation.

To actually measure the broad range of changes in health from a change in the HAP due to an intervention would require large, complicated, expensive, long-term field studies, particularly as the prevalence of most of the chronic diseases known to be exacerbated by HAP (COPD, IHD, LC, stroke) take many years to develop but also many years to decline with reductions in exposure. There is nevertheless a need for methods to credibly estimate the likely degree of ill-health that could be avoided by an intervention using the best available scientific evidence from epidemiological studies that could be expected from an intervention.

In this chapter, we describe the development pathway and methodology used in the Household Air Pollution Intervention Tool (HAPIT), an internet-based platform[6] to evaluate and compare health benefits achievable through reduced exposures to fine particulate matter ($PM_{2.5}$) resulting from implementation of fuel and/or stove interventions. It can be tailored to the conditions in each of many dozens of LMICs to give organizations contemplating interventions a rough, but credible, estimate of the comparable health benefits that could be accrued through each scenario.

The idea behind HAPIT is not to provide research-quality evidence of health benefits for all possible situations, which would take many years and involve costs and expertise that is well beyond that possible for most planned interventions. Rather, it aims to provide "good enough" evidence, based on the best available health effects information linked to air pollution exposures. There is a long tradition of using such risk assessment techniques to evaluate environmental health hazards, not only in air pollution[77] but from interventions to reduce water pollutants, radiation, toxic chemicals, and so on.

Evaluations of projects to reduce another important environmental health risk also benefit from such tools. Interventions to mitigate climate change use CO_2-equivalent metrics to estimate their benefits. They are not required to show an actual impact on climate change, which would take sophisticated studies lasting many years, but rely on associations established by the best current science between emissions of greenhouse gases and changes to climate. These come from complex climate models informed by measurements and that are evolving over time. Just so with HAPIT, which relies on the best intermediate variable between HAP and health, exposure to $PM_{2.5}$. Exposure is closely linked to the intervention in one direction and to health impacts in the other direction, via complex published models, based on major reviews of published health studies, which, like climate change models, evolve over time.

HAPIT outputs can be made available to policy makers in order to raise awareness about the potential public health implications of an intervention program at a national level, inform them about the health benefits expected from scaling up available interventions, and provide information on the relative costs of scaling up different intervention options. As such, there is a clear role for such a tool to inform health policy makers in the implementation of the World Health Organization's Indoor Air Quality Guidelines for household fuel combustion. Beyond the health sector, this tool can be used by clean cooking implementers both to help design better interventions (how clean do they need to be to achieve health benefits) and potentially to help raise funds to implement dissemination projects through results-based financing.

HAPIT estimates both averted DALYs and averted premature deaths and calculates a simple cost-effectiveness metric based on the World Health Organization's Choosing Interventions that

[6] HAPIT can be accessed at http://hapit.shinyapps.io/HAPIT

are Cost-Effective (WHO-CHOICE) framework. For illustration, here we demonstrate use of HAPIT to evaluate a chimney stove intervention deployed as part of the RESPIRE randomized controlled trial and an LPG intervention, both in the Western Highlands of Guatemala. Finally, we conclude with a discussion of the methodological and conceptual issues raised by HAPIT in the context of broader health and sociopolitical concerns and introduce the potential for results-based financing, based on averted DALYs, or aDALYs.

5.2 Methods

HAPIT relies (1) on up-to-date national background health data and (2) on the methods and databases developed as part of the Comparative Risk Assessment (CRA), a component of the Global Burden of Disease (GBD 2010). HAPIT utilizes exposure-response information for each of the major disease categories attributable to particulate air pollution and 2010 background demographic, energy, and economic conditions for the 57 countries in which solid fuels are the primary cooking fuel for 50% or more of homes [1]. HAPIT additionally includes a number of countries in which household energy intervention disseminations are underway or planned, but which have less than 50% solid fuel use nationally. All data are for year 2010, the most recent year for which country-level data are currently available from GBD. Figure 5.1 visually depicts HAPIT inputs and methods.

Background data used by HAPIT

All background disease information employed in HAPIT was downloaded from the Institute for Health Metrics and Evaluation's (IHME) GBD 2010 Country Databases[7]. The deaths and DALYs from lung cancer include the GBD 2010 estimates of tracheal, bronchial, and lung cancers. Cardiovascular diseases are broken down into two categories – Ischemic Heart Disease (IHD) and Ischemic & Other Hemorrhagic Strokes (Stroke). HAPIT calculates deaths and DALYs due to ALRI only among the population of ages 0-4. Average household sizes were extracted from the Global Alliance for Clean Cookstoves' Data and Statistics website[8]. Population data were extracted from the US Census International Bureau[9] and the UN's World Urbanization Project[10].

Cost-effectiveness is determined by comparing the expected annual cost of the intervention per averted DALY (described below) in USD to the gross domestic product per capita (GDP PC, USD). WHO-CHOICE advises that interventions costing less than the GDP/capita are very cost-effective, those costing one to three times the GDP/capita are cost-effective, and those costing more than three times the GDP/capita are not cost-effective [78].

HAPIT estimates program cost-effectiveness using a financial accounting approach. In doing so, it (1) does not take into account changes in household costs due to medical expenditure or the time or money spent acquiring fuel and (2) assumes that programs are covering the cost of fuel-

[7] http://ghdx.healthdata.org/global-burden-disease-study-2010-gbd-2010-data-downloads
[8] http://cleancookstoves.org/country-profiles/
[9] http://www.census.gov/population/international/
[10] http://esa.un.org/unpd/wup/

based interventions (such as monthly LPG costs per household). For custom scenarios, to take into account these parameters based on the characteristics of their programs, users can adjust the per-household maintenance or fuel costs. For example, the total financial outlay of the intervention program may decrease if households pay for a portion of the cost of the fuel or intervention, or pay back the cost over time. This can be accounted for in HAPIT by adjusting the per-unit or maintenance costs associated with the program.

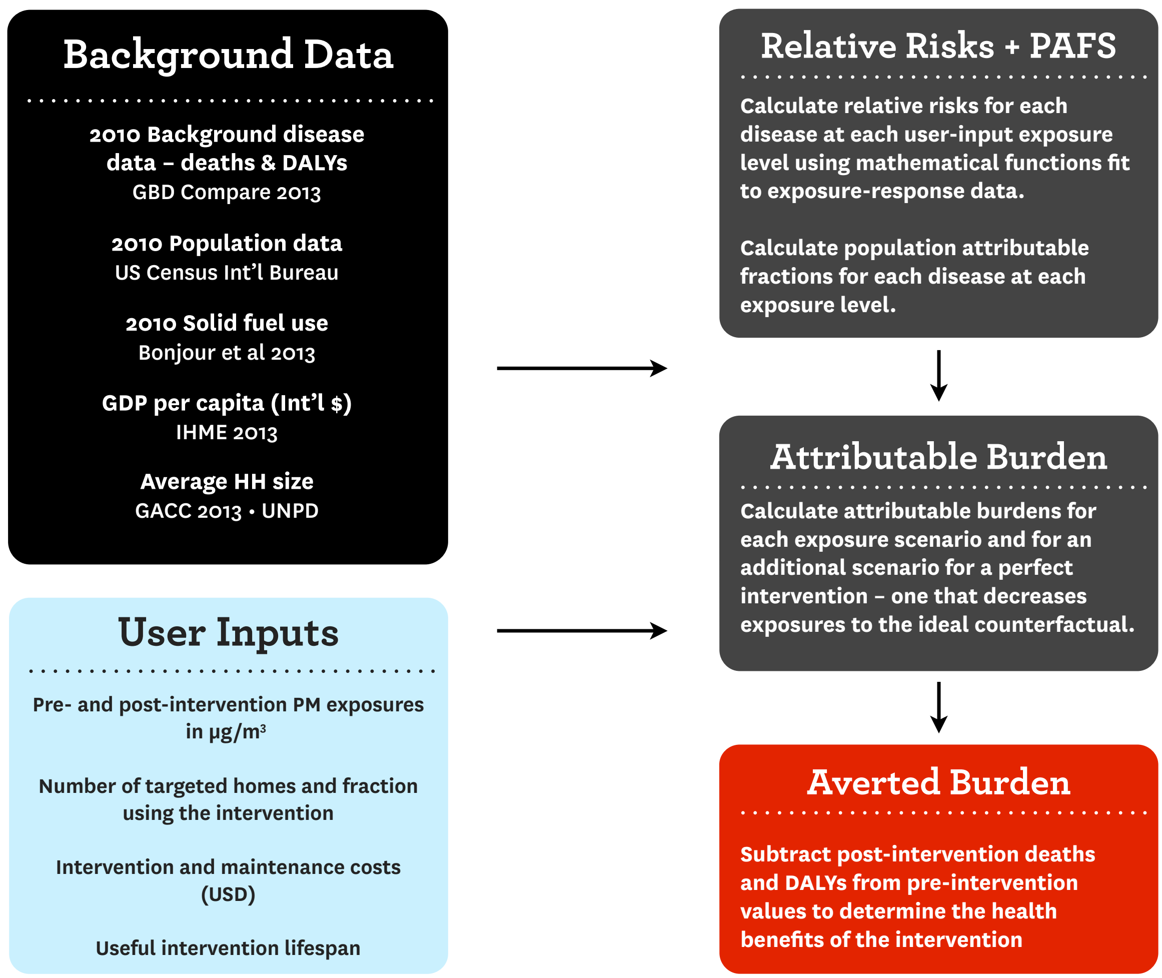


Figure 5.1 **HAPIT inputs and outputs**
A conceptual diagram of the inputs, outputs, and methods used to estimate averted ill-health using HAPIT.

User inputs
HAPIT users are able to input (1) pre- and post-intervention population average exposures to $PM_{2.5}$ in µg/m^3, based on measurements performed in the target communities, and the standard deviation of those measurements; (2) the number of households targeted by the intervention; (3) the average percentage of the population using the intervention throughout the intervention's

useful lifetime; (4) the cost to the program per intervention in current US Dollars (USD); and (5) the yearly maintenance cost (including fuel costs) per household in current USD. For users with limited data for these inputs, default values are available for each of these 5 items.

Users are strongly urged to address the following issues prior to scaling up an intervention:

- Intervention Effectiveness: selected interventions should have the ability, under ideal (laboratory) conditions, to reduce emissions of health damaging pollutants to acceptable levels [9,57]. Interventions that perform poorly in the laboratory are unlikely to perform well in the field.

- Intervention Acceptability: interventions should be evaluated in the community, to ensure appropriateness for local cooking and otherwise to suit local needs

- Exposure Reduction: in pilot work in the target community, or one like it, interventions should result in a demonstrable and significant reduction in population $PM_{2.5}$ exposures

- Sustained Intervention Usage: Interventions should, ideally, displace use of the more polluting traditional stove. Declining usage of the intervention over time may indicate reversion to traditional cooking methods and an elimination of any meaningful exposure reductions.

Because HAPIT relies on measured exposures to estimate averted ill-health, we briefly clarify the distinction between (a) emissions, (b) concentrations, and (c) exposures in the context of household air pollution studies:

a. <u>Emissions</u> refers to the rate of release of a pollutant per unit time or per unit of fuel; emissions measurements are often taken 'directly' from the combustion source and can be performed in the laboratory or the field. Although emission measurements can be conducted over an entire day, it is most common to conduct them in conjunction with one cooking cycle, either typical to the area if done in the field or with a standard cooking cycle if done in the lab.

b. <u>Concentrations</u> are a result of emissions and various room conditions, like ventilation rates, and processes, like deposition and exfiltration. Concentrations are often measured in microenvironments – for instance, in the kitchen and in the living room – but do not directly take into account the presence of people. Because it is difficult to simulate real world situations, reliable concentration measurements normally are measured in households themselves. Commonly, for example, kitchen air pollution (KAP) measurements are made by placing a monitor on the wall of the kitchen for 24 hours.

c. <u>Exposures</u> are complex, spatiotemporal relationships between individuals and the concentrations of pollutants in their vicinity. A population exposure thus depends on the concentration of pollutant in an area, the number of people in the area, and the time spent in that area. Similarly, an individual's daily exposure is impacted by the variety of sources they experience in the spaces they inhabit for varying lengths of time throughout the day. For example, high concentrations of pollutants in a smoky kitchen do not necessarily result in high exposures; if the cook spends most of her time outside of the kitchen, her average exposure may not be as high as a concentration may predict. Exposure involves contact between humans and pollution. Because of the nearly universal diurnal pattern of human activity, exposure monitoring is best done for at least 24 hours or multiples of 24 hours (48, 72, etc).

Data on lab-based emissions, although fewer than desirable, are increasingly publicly available (catalog.cleancookstoves.org). In contrast, the availability of exposure data across a range of geographies, fuel and stove combinations, and cooking practices remains limited, especially for the most promising (based on lab performance) stoves and fuels. Moreover, given the complexity of exposure characterization and the paucity of available data linking exposures and emissions, it is not currently possible to reliably estimate exposures from lab-based emissions data without extensive measurements followed by modeling at the local level. Default exposures in HAPIT are based on the available literature and informed largely by global modeling of HAP exposures [2,79].

Integrated exposure-response functions

Estimating the burden of disease attributable to all types of air pollution – including household air pollution (HAP) – during the 2010 Global Burden of Disease required elaboration of integrated exposure-response (IER) relationships [13] that relate $PM_{2.5}$ exposures to risk for a number of health endpoints. The IERs leverage epidemiological evidence from a wide range of $PM_{2.5}$ exposures spanning multiple orders of magnitude (ambient air pollution, active and secondhand tobacco smoke, and household air pollution) and result in supra-linear exposure-response curves (Figure 5.2).

In Burnett et al. (***14***) the parameterization of the IERs took a common form:

$$(1)\quad RR_{IER}(z) = 1 + \alpha\,\{1 - \exp[-\gamma\,(z - z_{cf})^{\delta}]\}$$

where z is exposure to $PM_{2.5}$ in μg/m^3, z_{cf} is the counterfactual exposure to $PM_{2.5}$ in μg/m^3, and where α, γ, and δ are model parameters. In initial versions of HAPIT (version 1 and 2), Eureqa (Nutonian, Inc.) was used to fit a line to a table of central relative risk estimates (and lower and upper confidence bounds) provided by Burnett et al. (14) for concentrations ranging from 0 to 1000 μg/m^3. In version 3 of HAPIT, we utilize data released by the Institute of Health Metrics and Evaluation (IHME) to create a lookup table of relative risks, using methods similar to those reported elsewhere [80]. For each health endpoint – and for twelve age-categories for IHD and Stroke – 1000 values of z_{cf}, α, γ, and δ were provided [81]. We calculated the lower bound (5th percentile), central (mean), and upper bound (95th percentile) relative risk estimates from the distribution of provided values for each health endpoint, age-category, and for exposures ranging from 1 to 1000 μg/m^3 in discrete 1 μg/m^3 steps. For concentrations less than the counterfactual concentration of 7.3 μg/m^3, the relative risk was fixed at 1, indicating no difference in risk.

Evaluating averted ill-health

HAPIT generates 1000 paired pre- and post-intervention exposures by sampling from a lognormal distribution reconstructed from the user input mean exposure and measurement standard deviation. For each pair of exposures, HAPIT identifies the corresponding relative risks from the look-up table. The population attributable fraction (equation 2) is then calculated as follows:

$$(2) \qquad PAF = \frac{SFU(RR-1)}{SFU(RR-1)+1}$$

where SFU refers to the percent of the population using solid fuels and RR refers to the relative risk calculated using the IERs. The approach utilized is based on methods developed by the GBD and others [82,83], but adapted to take advantage of the continuous IER functions.

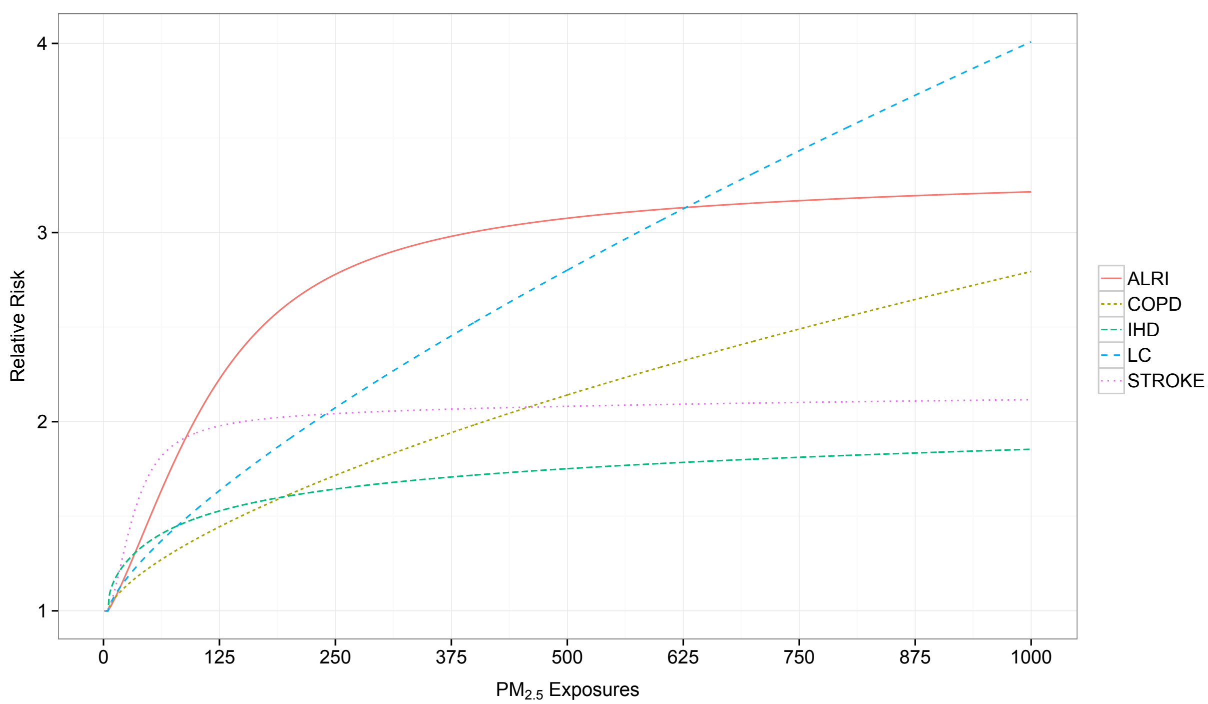


Figure 5.2 IER curves relating exposure to $PM_{2.5}$ to health endpoints
Health endpoints associated with exposure to air pollution include ischemic heart disease (IHD), stroke, chronic obstructive pulmonary disease (COPD), and lung cancer (LC) in adults and acute lower respiratory infection (ALRI) in children. See Figure 5.4 for an elaboration of uncertainties around the IERs.

To estimate changes in deaths and DALYs attributable to an intervention (AB_{int}), we subtracted the PAF after the intervention ($PAF_{post\text{-}intervention}$) from the PAF prior to the intervention ($PAF_{pre\text{-}intervention}$) and multiplied by the user input usage fraction; the underlying disease burden

($B_{endpoint}$) for a specific country, health endpoint, and age-group as follows; and the percentage of solid-fuel use in the target population:

$$(3)\quad AB_{int} = (PAF_{pre\text{-}intervention} - PAF_{post\text{-}intervention}) \times B_{endpoint} \times Use_{fraction} \times SFU_{fraction}$$

Averted burdens are calculated for all combinations of the lower, central, and upper relative risk estimates and the central background disease rate estimates for each of the 1000 exposure pairs. HAPIT outputs the following:

(a) the mean averted deaths and DALYs - the mean of the 1000 attributable burdens calculated using the central relative risk

(b) the minimum averted deaths and DALYs – the mean of the 1000 attributable burdens calculated using the lower bounds of the IERs

(c) the maximum averted deaths and DALYs – the mean of the 1000 attributable burdens calculated using the upper bounds of the IERs

(d) the maximum avertable deaths and DALYs – the burden that could be averted by going from the pre-intervention exposure to the counterfactual, assuming 100% stove usage

HAPIT assumes that all deaths and DALYs due to ALRI are accrued instantaneously upon implementation of the intervention. For chronic diseases in adults (COPD, stroke, IHD, and lung cancer), HAPIT utilizes the 20-year distributed cessation lag model of the United States Environmental Protection Agency (US EPA), a step function for estimating the accrual of benefits due to changes in exposure to air pollution (Figure 5.3). The EPA model assumes that 30 percent of mortality reductions occur in the first year, 50 percent are distributed evenly in years two through five, and the remaining 20 percent are distributed evenly in years six through twenty [84]. At the end of the intervention's lifetime, we assume that benefits for children from reduced ALRI cease; an additional 75% of a full benefit-year accrue for chronic diseases.

HAPIT limits an intervention's useful lifetime to, at a maximum, 5 years. This is due to two issues. First, because attributable burden calculations rely on up-to-date background disease information, extending beyond five years unrealistically assumes no change in background disease rates. Second, evidence from the field indicates that many current interventions do not have a useful life beyond two or three years [43,85] at most.

Disability-Adjusted Life Years

While HAPIT outputs averted deaths, a perhaps more interesting and useful output is that of averted DALYs. The DALY is a combined metric of mortality and morbidity that measures the gap between the 'ideal' and the experienced health states of a population. DALYs are composed of two parts, years of life lost (YLLs) to premature death and years lived with disability (YLDs) weighted by the severity of the condition experienced. Fundamentally, the DALY seeks to put death and disability from all diseases on an equal footing for all individuals of the same age in the world, irrespective of social class, country of origin, socioeconomic status, occupation, or other characteristic [86]. GBD 2010 used a life expectancy at birth of 86 years to calculate YLLs and, unlike previous GBD undertakings, removed all discounting and age-weighting [87]. The calculation of disability weights was updated to take into account global heterogeneity in perception of the severity of various conditions and utilized revised methods by which surveys were translated into severity weights. While a number of concerns about the use of the DALY remain [88], to date no other combined metric of morbidity and mortality has been as thoroughly described and used in global health literature. Use of the DALY allows simple comparisons of cost-effectiveness across sectors and potential interventions and is commonly used in the global health literature.

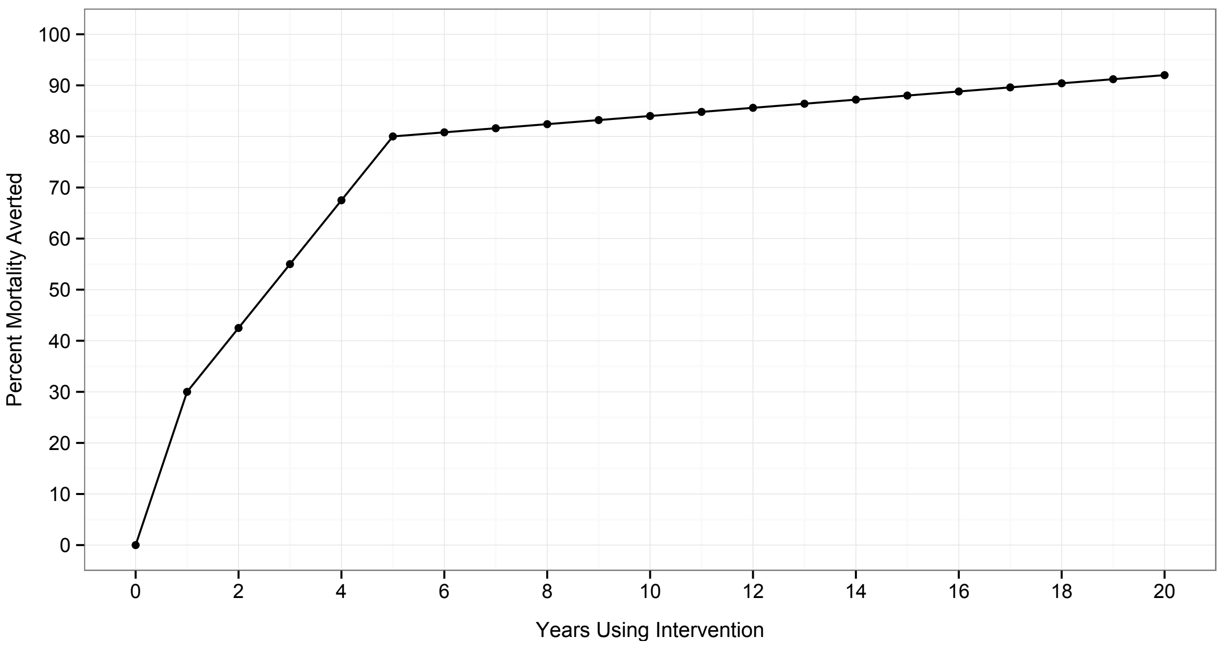


Figure 5.3 Visual representation of the EPA 20-year cessation lag function
The cessation lag function as outlined by the US EPA [84] is used to adjust downward the attribution of averted DALYs and Deaths from chronic disease due to reduced $PM_{2.5}$ exposures resulting from an HAP intervention.

Implementation of HAPIT

The basic calculations for HAPIT are implemented in R (3.1, [71]) and utilize Shiny, a framework enabling sharing of interactive R code over the internet [89]. HAPIT is currently hosted by RStudio for a nominal monthly fee. Figures are generated using ggplot2 [90].

5.3 Findings from two hypothetical scenarios

Overview

As an illustration of the use of HAPIT, we adapt findings from the Randomized Exposure Study of Pollution Indoors and Respiratory Effects (RESPIRE), a randomized control trial (RCT) that assessed the impact of reduced emissions from a chimney stove on childhood pneumonia [8], and subsequent studies in the region [42,45,61,91]. The study design has been described extensively elsewhere [92,93]. Briefly, it took place in the Western Highlands of Guatemala between October 2002 and December 2004. Most study homes were located between 2000 and 3000 meters above sea level and used wood as their primary cooking fuel. 518 households contributed to the final dataset, with approximately half receiving a chimney stove and the other half cooking with a traditional open fire. Across Guatemala, 64% of households rely on solid fuel for cooking. The GDP per capita in Guatemala is approximately 5000 USD.

Scenario inputs

While carbon monoxide (CO) exposures were the primary exposure measurement collected during RESPIRE, $PM_{2.5}$ exposures were also assessed at various points throughout and after the primary RESPIRE trial, as described in McCracken et al (2007, 2011). For this analysis, we assume any new chimney stove implemented in the region would perform similarly to findings during those assessments; that is, we expect to see adult exposure reductions to $PM_{2.5}$ from 264 µg/m^3 (SD = 297) when using the traditional stove to 102 µg/m^3 (SD = 130) when using the intervention chimney stove[11]. For children, we use the ratio of child to mother exposures to carbon monoxide to scale exposure reductions appropriately. Because of the rich data available on CO exposures, we are able to estimate mother-to-child ratios for both the pre-intervention and post-intervention periods. During the pre-intervention period, child exposures are ~45% of the mothers' exposures; in the post-intervention period, child exposures are ~54% of the mothers' exposures. Accordingly, for children, the pre- and post-intervention $PM_{2.5}$ exposures are estimated to be 119 µg/m^3 (SD = 133) and 55 µg/m^3 (SD = 70), respectively.

We additionally assume the intervention will reach 25,000 households, be used consistently by 90% of households [21], have a 5-year lifespan, cost 200 USD per intervention stove, and have a maintenance cost of 5 dollars per year per intervention stove. For comparison, we will also consider an LPG intervention that reduces exposures of both mothers and children to the level of ambient pollution in these communities of 30 µg/m^3 (SD = 20)[12], also has a 5-year useful lifespan and 90% fraction of households using the intervention, and costs 75 USD per stove, with a fuel cost of 175 USD per year per household. Inputs for both scenarios are summarized in Table 5.1.

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[11] Application of HAPIT should ideally include up-to-date personal exposure measurements of $PM_{2.5}$.

[12] The post-intervention concentration in this LPG scenario may seem counter-intuitive: LPG has been shown to very clean and emit almost no particles when operated properly. Why, then, not reduce the exposure to the ideal, 7.3 µg/m^3 counterfactual? In this case, we assume some pollution arises from households in the community who may not have transitioned to LPG or from other sources, such as trash burning, power generation, or vehicles, to name a few possibilities. LPG exposure reductions for this example are set to background ambient $PM_{2.5}$ concentrations as measured during RESPIRE.

Findings

Figure 5.4 depicts the simulated exposures before and after distribution of the chimney-stove intervention. The depicted IERs illustrate the non-linear nature of expected health-benefits associated with an exposure reduction. For instance, for adults, the relationship is relatively 'flat' for Stroke and IHD for an exposure reduction due to the intervention stove. For COPD and lung cancer in adults and ALRI in children, the relationship is relatively linear, though the slope varies. For all health endpoints, the uncertainties are large and variable depending on the location on the curve corresponding to a specific exposure.

Table 5.1 HAPIT inputs for chimney stove and LPG interventions in rural Guatemala

	Pre-Intervention Exposure μg/m³ (SD)		Post-Intervention Exposure μg/m³ (SD)		# Homes	Avg. Use %	Stove Lifetime (yrs)	Initial Cost USD	Yearly Cost USD
	Adults	Kids	Adults	Kids					
Chimney	264 (297)	118 (113)	102 (130)	55 (70)	25,000	90	5	200	5
LPG			30 (20)					75	210

Assumptions

In the above examples, we do not consider the common practice of stove stacking, which would result, most likely, in higher post-intervention exposures. We do not include costs or savings to households, which may include time saved and be put towards other productive activities. Additionally, we do not consider dissemination costs or monitoring and evaluation costs, though as mentioned above we do assume that fuel costs are covered by the program. We assume that background disease rates for all of Guatemala are applicable to this region.

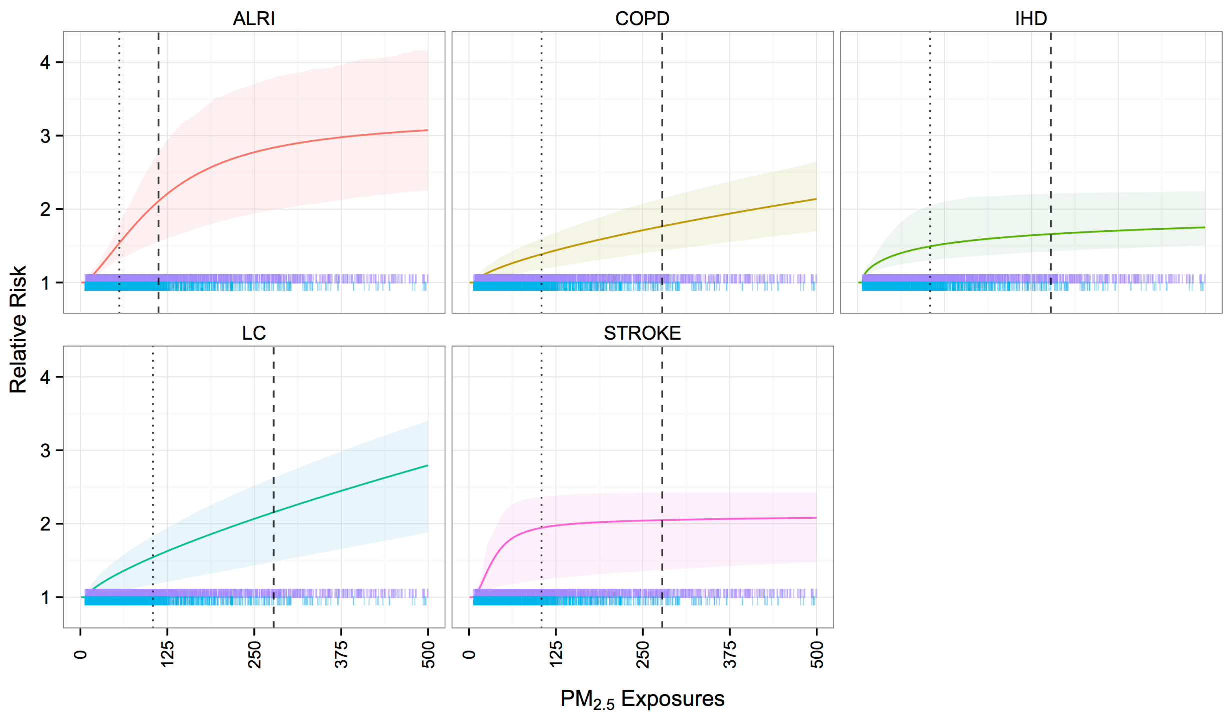

Figure 5.4 IER curves and uncertainty bounds (lightly shaded)
The dashed vertical line indicates the pre-intervention exposure; the dotted vertical line indicates the post-chimney intervention exposure. The upper and lower tick marks along the x-axis are the distributions of the simulated pre- and post-intervention exposures, respectively.

Estimates from HAPIT suggest that dissemination of 25,000 chimney stoves – similar to those used during the RESPIRE RCT – with 90% usage, no stove stacking, and a 5-year lifespan would avert approximately 3335 DALYs (uncertainty bounds 1855 – 4520) and 72 (uncertainty bounds 37 – 94) deaths given the exposure reductions modeled above. The majority of the health benefits result from reductions in ALRI in children under 5 (Table 5.2). Figure 5.5A displays the Averted DALYs and Deaths by disease category and the burden remaining for each group. On average, approximately 72% of the burden remains, though there is heterogeneity between disease categories (range: 62 – 85%). When using the least conservative estimate, approximately 62% of the burden still remains. Similarly, 57% (range: 57 – 75%) of the burden remains if trying to reach 30 μg/m^3, the level of background ambient pollution in RESPIRE communities.

Table 5.2 HAPIT outputs for chimney stove and LPG stove interventions in Guatemala

	ALRI		COPD		IHD		Lung Cancer		Stroke	
	DALYs (range)	Deaths (range)	DALYs (range)	Deaths (range)	DALYs (range)	Deaths (range)	DALYs (range)	Deaths (range)	DALYs (range)	Deaths (range)
Chimney	2385 (1290-3230)	30 (15-40)	240 (180-290)	7 (5-10)	380 (240-580)	20 (10-25)	80 (50-90)	3 (2-4)	250 (95-330)	12 (5-15)
LPG	3900 (2570-4780)	45 (30-55)	390 (290-470)	12 (8-14)	730 (540-1150)	35 (25-55)	130 (85-150)	5 (4-6)	600 (280-660)	30 (15-30)

For an LPG dissemination of 25,000 stoves with 90% usage, no stove stacking, and a 5-year lifespan, HAPIT estimates approximately 5750 DALYs (uncertainty bounds 3765 – 7210) and 127 deaths averted (uncertainty bounds 82 – 160). Figure 5.5B displays the Averted DALYs and Deaths by disease category for an LPG intervention as described. On average, approximately 52% percent of the burden remains (range 39% – 69%). When using the upper bound estimate of the potential impact of an LPG intervention, approximately 39% of the burden remains. Contrastingly, the ill-health remaining on the table relative to ambient air pollution is only approximately 16%. This latter would be taking ambient air pollution as the counterfactual, i.e. the minimum achievable by a change within the household itself.

Despite its large unaverted burden, the chimney stove intervention is considered 'very cost effective' across its entire range of potential averted DALYs using the simple WHO-CHOICE rubric (Figure 5.6A). The LPG stove intervention is also considered very cost-effective, though the range of uncertainty around this estimate is greater than for the chimney stove (Figure 5.6B), extending into the "cost-effective" range. This is because the LPG, unlike biomass, is not free. The LPG intervention is sensitive to price variation; if the January 2015 price for an LPG cylinder is used (18 USD), the intervention and its uncertainty bounds move entirely into the "cost-effective" category. In these examples, the households may be willing to bear part of the cost of either a chimney stove or LPG stove and/or the monthly cost of the LPG, thus reducing the direct cost to the program itself and impacting program cost-effectiveness estimates.

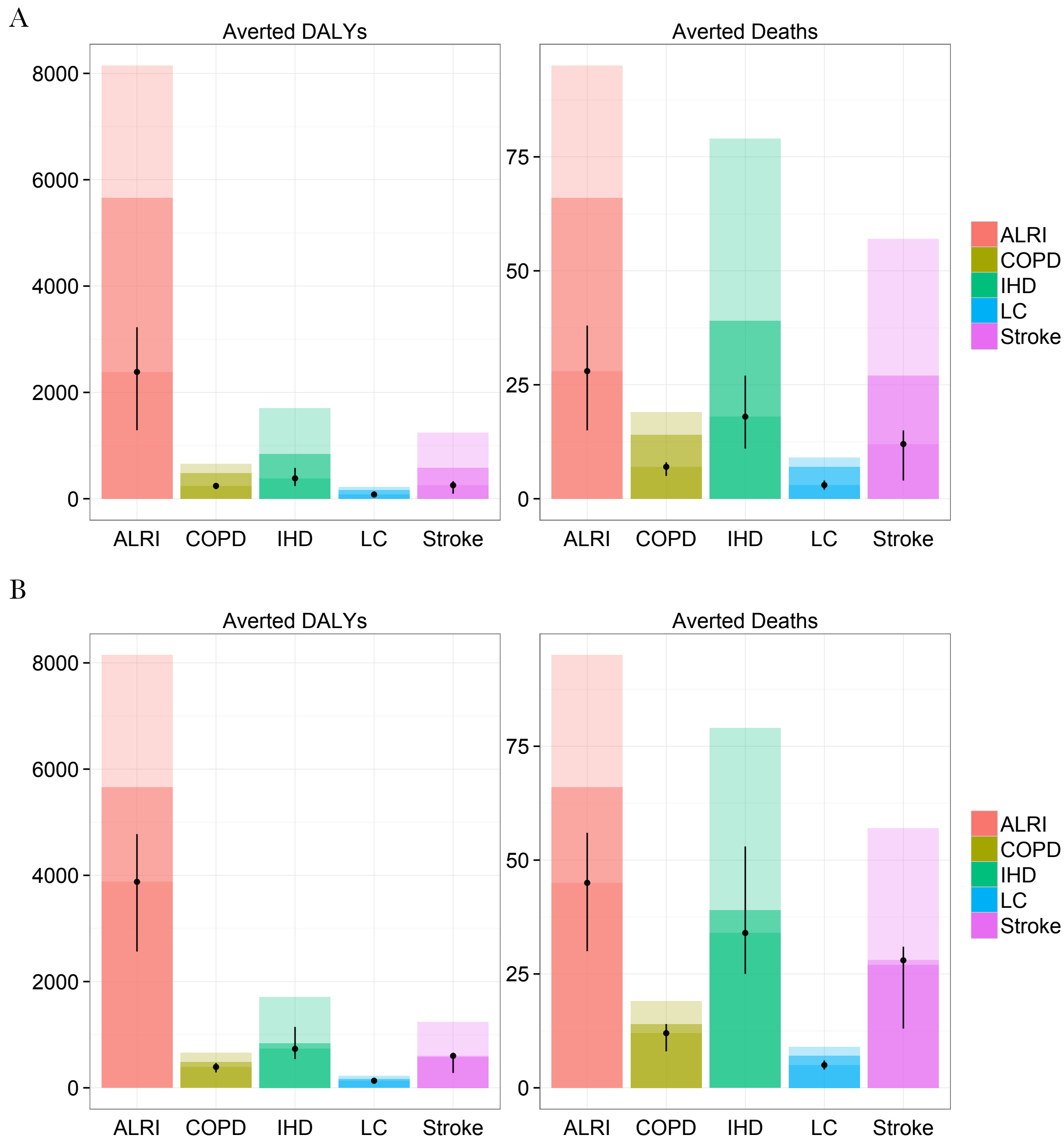

Figure 5.5 Averted deaths and DALYs by disease category for two scenarios
(A) a chimney stove intervention and (B) an LPG stove intervention in Guatemala. The darkest bars are the central estimate of averted ill-health; the lightest bars are the total burden avertable by the best possible intervention – one that gets down to the counterfactual exposure of 7 μg/m³. The remaining bar represents the burden left by an intervention that gets down to 30 μg/m³, the outdoor ambient level measured during RESPIRE. Vertical lines indicate the range of averted ill-health attributable to the intervention modeled by HAPIT.

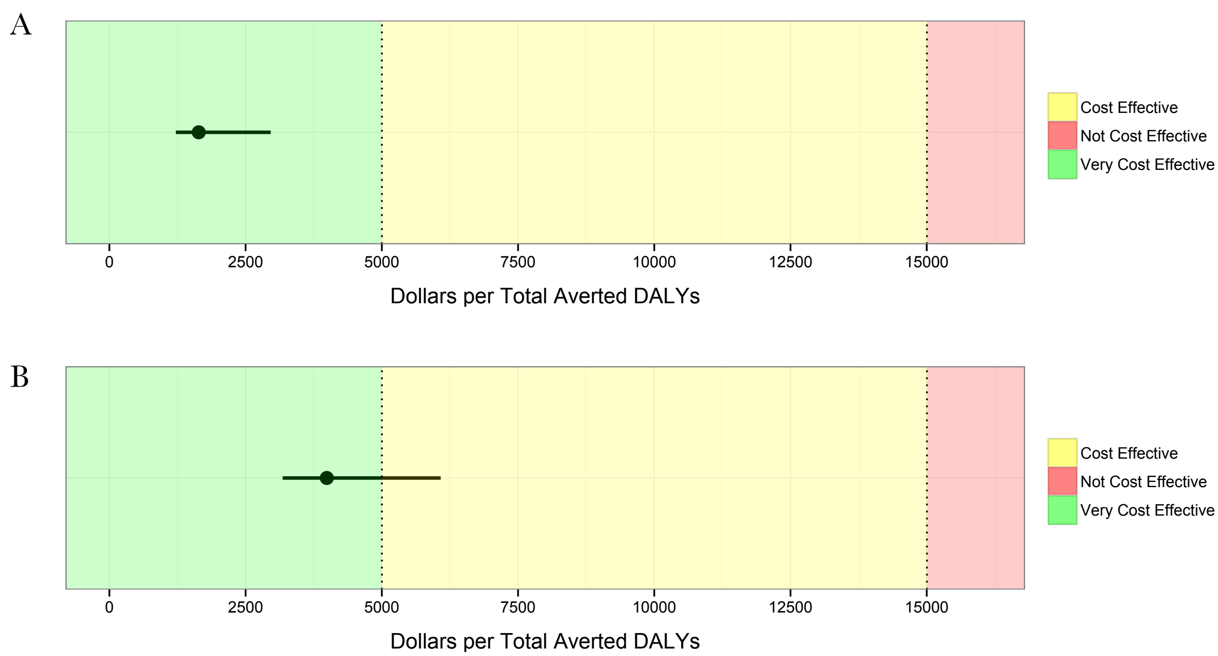

Figure 5.6 Dollars per total averted DALYs
The green shading indicates the WHO-CHOICE "very cost-effective category" (< GDP PC per DALY), the yellow shading indicates the "cost-effective" category (between 1 and 3 x GDP PC per DALY) and the red indicates "not cost-effective." Panel A is for the chimney stove intervention; Panel B is for the LPG intervention. The 2010 GDP PC in Guatemala was approximately 5000 USD.

5.4 Considerations arising during the development and use of HAPIT

HAPIT provides an easy-to-use, web-accessible format for assessing the impact of a household air pollution intervention for countries in which there is a significant solid fuel-using population. It estimates a range of DALYs and deaths averted by an intervention based on epidemiological methods and using the best available background disease and exposure-response data available. The somewhat simple interface masks significant computational and methodological complexity, and should thus be used with care when making significant policy decisions and considering large interventions with substantial financial and logistical costs.

During the development of HAPIT, a number of methodological and conceptual issues came to the fore. We conclude with a discussion of these issues, of the limitations of HAPIT, and of next steps to further enhance the robustness and reliability of HAPIT-based estimates.

Assumptions and limitations of HAPIT
HAPIT makes a number of assumptions and has a number of limitations. The most prominent follow.

(1) HAPIT assumes that measurements of changes in exposure made over a short period of time are indicative of long-term trends. For results-based financing centered around using averted DALYs and deaths, it will be necessary to perform periodic verification of benefits throughout the period of time financing is sought.

(2) As currently designed, changes in exposure to the cook, upon whom measurements were taken, reflect changes in other household members. The impact on children under the age of 5 is adjusted by the default relationship described above for all scenarios in HAPIT unless an alternate ratio is provided. It is strongly suggested that any alternate ratio be grounded in measurements.

(3) HAPIT assumes background disease and economic characteristics are relatively static. For interventions with a short life-span, this assumption may hold; for long-lived interventions, such as transitioning a community to clean fuels or electricity, HAPIT estimates would need to be revised regularly. In addition, economies of scale are not considered when evaluating cooking interventions costs. Human development indicators may change rapidly depending on social, economic, and political conditions in countries in which HAPIT may be used. These changes can impact the relative merits of a HAP intervention, swaying an intervention from not cost-effective to cost-effective (or vice versa) based, for example, on more recent GDP per capita estimates or, for fuel interventions, on fuel costs. For example, the price of LPG in Guatemala has been fairly volatile, varying between 5 USD in 2003 and 18 USD in early 2015, before dropping back to 10 USD in May of 2015. HAPIT's simplistic cost-estimates do not currently account for monthly or yearly fuel price fluctuations.

(4) HAPIT currently relies on IHME's GBD of disease data, which is, as of now, the most complete and comprehensive burden of disease data available. This completeness comes with the price of some methodological opacity. Continued burden of disease efforts from the World Health Organization and others may result in more rigorous and open model comparison efforts, similar to those seen among climate scientists.

(5) The current method of estimating uncertainty in deaths and DALYs averted from the IERs does not fully utilize the distribution around each point in the IERs; in doing so, it may underestimate the minimum values and overestimate the maximum values. Alternate methods – including probabilistic analyses for each parameter in HAPIT, including a distribution of potential impacts at each point along the IERs – are discussed below.

HAPIT highlights the tension between cost-effectiveness and the burden left 'on the table.' As seen in both of the example scenarios above, deployment of a HAP intervention leaves significant ill-health in target communities. This "unaverted" burden poses a quandary to policy makers and health practitioners seeking cost-effective solutions to myriad health problems. In the example above, the chimney stove is more cost-effective by the admittedly simple form of WHO-CHOICE implemented here; however, it leaves a substantial health burden on the table. The LPG intervention, meanwhile, is less cost-effective, but removes more of this burden from the table. Some may argue that the chimney stove represents an incremental change toward cleaner energy systems; others may counter that leapfrogging attempts at cleanly burning biomass may represent the clearest path forward towards reducing the HAP-related health burden. Rather than make an argument in either direction, we highlight the types of fundamental questions that HAPIT brings to light. These questions are further complicated by considering other health programs − such as a rotavirus vaccine program, the widespread deployment of insecticide-impregnated bednets, efforts to improve access to pre-natal care services or a scale-up of a water purification device − side-by-side with HAPIT-based avoided ill-health estimates from clean cooking interventions.

As both interventions leave a significant portion of the burden on the table, we assume that there is some contribution to background ambient air pollution from unclean cooking in homes around intervention homes that contributes to exposures. Controlling this air pollution by, for example, ensuring widespread access to clean cooking fuels in a community could lead to more substantial benefits of an intervention. Put another way, deploying interventions to a larger fraction of homes may have the additional benefit of improving ambient air pollution enough to make an intervention more cost-effective. Further research is needed to better understand what proportion of population 'coverage' with and usage of an intervention would be needed to optimize intervention-related benefits. Finally, our consideration of the burden 'left on the table' explicitly acknowledges that reaching a state of no additional ill-health above the counterfactual would most likely require action to reduce all sources of air pollution − including ambient air pollution from non-cooking sources and pollution released by industries and vehicles, to name a few.

Complications are additionally introduced by an appliance-model of household energy use, in which interventions are used concomitantly with traditional cooking technologies to fully meet the cooking and heating needs of the household − a phenomenon known as stove stacking. As shown in a recent modeling exercise, occasional use of a traditional stove can lead to significant exposures [14]. HAPIT assumes displacement of the traditional stove for the percentage of households using the intervention. In homes where stacking occurs, HAPIT may over-predict potential health benefits. Part of this shortcoming is accounted for in the probabilistic approach used, in which 1000 exposures across the distribution of measurements are drawn to estimate averted health impacts. However, the potential impact of stacking to dilute potential exposure reductions has not been taken into account [43,94].

HAPIT estimates will evolve as GBD-provided background disease information and integrated-exposure response curves change over time. Forthcoming data from the 2013 GBD update will undoubtedly alter HAPIT estimates, as it includes a number of revisions to the way air pollution burdens are estimated. Updating HAPIT to account for changes in background disease rates estimated by GBD (and for updates to the IER curves) is a non-trivial task complicated by the unavailability of access to GBD data. Furthermore, updates to HAPIT may invalidate results from previous versions of HAPIT.

Future steps

More nuanced probabilistic uncertainty analysis is possible given the wide number of inputs (and corresponding uncertainty bounds) used in HAPIT estimates. Incorporating and propagating these uncertainties throughout the model, however, requires significant computational resources and would increase the requisite run time by 10 to 30 fold. We are evaluating methods to more quickly incorporate these types of uncertainty analyses in HAPIT by utilizing multi-core computing techniques.

An additional and less tractable complexity arises from the model-based uncertainty bounds generated by the IHME modeling of the GBD. As noted elsewhere [95,96], the uncertainties presented in the GBD 2010 are complex and challenging to interpret and use in further analyses of the type we describe. For some inputs, including the IERs and the WHO solid fuel use estimates, more methodological clarity is now available, and this will facilitate Monte Carlo and other simulation-based analyses.

Including reductions in community-scale ambient air pollution

A well-performing, well-used intervention may result in benefits to households not using the intervention by way of reductions in emissions contributing to ambient air pollution. Accounting for these benefits without a significant measurement campaign would be challenging, but is feasible. For example, exposure reductions due to reduced ambient pollution could be estimated by (1) measuring exposures of individuals present in communities where an intervention campaign is taking place, but who themselves did not receive an intervention and (2) by measuring ambient pollution in those communities continuously as the intervention campaign is implemented. These measurements are typically expensive, and would need to account for seasonal effects, though the benefits of such an effort could be substantial.

HAPIT does not currently have the capability to estimate these benefits, though they could be separately estimated in an analogous fashion to those stemming from an intervention. For instance, if measurements indicated that ambient concentrations were reduced from 264 $\mu g/m^3$ to 200 $\mu g/m^3$ for an additional 10,000 households (or a percentage of households without an intervention in a given community) receiving an intervention, HAPIT could be run using these measurements to estimate the additional averted DALYs and deaths attributable to the intervention's contribution to cleaning up the community airshed as a secondary benefit.

Sub-national or customized estimates using specific background disease data

For some countries – including India, Mexico, Peru, and Nepal – where national statistics may not adequately represent sub-national populations, the ability to customize background disease information may enhance HAPIT's reliability. We are exploring methods by which to incorporate this feature.

5.5 Conclusions

There is a growing focus on interventions seeking to reduce the burden of disease associated with household air pollution. HAPIT provides policy-makers and program implementers a relatively easy-to-use tool by which to compare the relative merits of programs both within and between countries, helping assist with optimization of limited resources. Although a number of uncertainties remain, HAPIT is intended to represent the 'state of the science' and rely on the best available knowledge – and is built to easily integrate new knowledge and findings to improve estimates.

HAPIT is freely available for use over the web and can output a summary report to guide later discussions. Like other publicly available tools used to assist in resource allocation and policy making decisions [54,97], though, it requires a significant understanding of the particulars of the community and country in which an intervention is proposed; confidence in the interventions' ability to reduce exposure to HAP; measurements of exposure to $PM_{2.5}$ before and after an intervention; and significant consideration of optimal ways to deploy and maintain an intervention over time.

Chapter 6
Discussion

6.1 Overview

The use of solid fuels as a household energy source continues to pose significant threats to human health and welfare. Despite progress towards clean cooking in many countries – including new strategies to increase use of LPG in Ghana and India and of electricity in Paraguay and Ecuador – it remains apparent that use of solid fuels will continue for the appreciable future for a large portion of the world's population. In places where a transition to clean cooking is occurring, there is a need to optimize impact evaluation and monitoring and evaluation techniques to provide high-quality evidence with minimum burden on participants and field staff.

Along these lines, there currently exists (1) moderate-to-high quality evidence linking $PM_{2.5}$ exposure from solid fuel use with adverse health outcomes and (2) laboratory and field evidence indicating modest reductions in $PM_{2.5}$ emissions, area concentrations, and exposures from available technical interventions. For the most part, these evidence bases are based on scientific research, and as such rely on intensive monitoring for significant periods of time.

This dissertation focuses, in part, on using data generated by low-cost, time-resolved sensor systems to unpack certain assumptions behind these existing evidence bases. Chapter 2 investigates the appropriateness of the current standard practice of using a single, short-term measurement of PM concentration as a proxy for the long-term average – and finds it lacking. Chapter 4 emphasizes the necessity of evaluating the use of interventions both over time and in conjunction with use of the traditional, more polluting stove, in order to understand more fully the potential for exposure reductions. As recent work has shown[14], even occasional use of a traditional stove can outweigh benefits of a clean stove. This poses a significant challenge to policymakers and interventionalists, who must both encourage use of the clean stove and discourage use of traditional sources. Additionally, both Chapters 2 and 4 consider tradeoffs between continuous monitoring, which generates large volumes of data at considerable expense and inconvenience, and "smart" sampling strategies that capture enough variability to meaningfully evaluate an intervention and are of the type appropriate for the large-scale monitoring required of rapid transitions like those occurring in India and Ecuador.

A second focus of this dissertation is to provide methods for evaluating interventions in the field. Chapter 3 describes initial, mixed-methods pilot worked we performed in Haryana, India to assess two potential interventions for a larger scale deployment (described in Chapter 4). While relatively straightforward, the chapter highlighted the vital importance of thorough, involved pilot work prior to selection of a technology. Of the two evaluated technologies, one was clearly not preferred and not used, despite its impressive performance during laboratory testing. The second, while used consistently and well-liked by pilot participants, suffered from numerous mechanical and technical failures throughout the large deployment. These problems may have been avoided with even more in-depth pilot work and reliability testing.

Chapter 5, meanwhile, describes HAPIT, a software tool that allows policy makers and intervention implementers to weigh the potential impact of deployment of a clean cooking technology at scale. HAPIT requires pilot work – slightly more involved, though similar to, the work described in Chapter 3 – to understand the true performance of an intervention under conditions similar to an actual deployment at scale. It provides an estimate of ill-health that could be avertable by the intervention. In doing it so, it (1) allows governments, NGOs, and implementing agencies to weigh the potential benefits of an intervention and (2) provides a new venue for results-based financing.

6.2 Measurement strategies

Chapters 2 and 4 describe long-term monitoring of parameters that impact exposure to $PM_{2.5}$ over timeframes much longer than such monitoring is normally performed. While we recommend these types of assessments for future academic studies, one goal of both chapters was to better understand how little measurement was, in fact, adequate to understand long-term trends. In both chapters, we found substantial variability within and between homes.

In the case of continuous $PM_{2.5}$ measurement, this practically meant that the standard practice – of sampling for 24 or 48 hours in a home – was inadequate to truly capture the variability in home. For our long-term deployment of stove use monitors, the situation was complicated by the disruption we introduced into kitchens in the form of an intervention. The ability to assess how well a short-term measure of use predicted true long-term use was distorted. However, the picture of changing patterns of use over time – with an initial spike that declined steadily – remained important and highlighted the dynamic nature of interventions (especially an intervention that suffered from profound mechanical and maintenance-related issues).

An unintended (and happy!) consequence of dealing with the large volumes of data created during these measurement campaigns was development of a set of R-based tools to ingest, manage, and analyze large volumes of data. These tools – along with user friendly, graphical versions of them – are freely available at github.com/ajaypillarisetti.

6.3 Evaluating interventions

Chapters 3 and 4 describe the process by which an intervention stove was selected for deployment in rural Haryana, India and how that deployment proceeded with regard to adoption of that stove. Chapter 5, meanwhile, describes a way to consider a stove intervention by modeling the potential health benefits attributable to its deployment. This type of modeling requires significant pilot work to understand how the stove is used over time (requiring techniques and tools similar to those described in Chapter 4) and how the intervention impacts personal exposures to $PM_{2.5}$ and how it is perceived by study participants (using methods similar to those described in Chapter 3).

Wide-scale deployment of SUMs, as described in Chapter 4, required more intensive household visits, manpower, and data handling care than initially anticipated. Projects seeking to undertake a similar scale of monitoring should take into account the potential for significant data loss and adjust personnel schedules accordingly. For instance, more frequent visits to homes – say once per week – can help detect failed or removed sensors and minimize the amount of data loss. However, increasing the number of home visits requires more field staff and excellent logistics, and may be difficult if studies are spread over wide geographic areas.

Moving forward, study designers should considered staggered sampling intensities. Like the study described in Chapter 4, we strongly suggest sampling in homes for at least two weeks prior to deployment of an intervention. Understanding the pre-intervention traditional stove usage patterns enables researchers and program implementers to evaluate how traditional stove use changes over time. During the initial weeks following introduction of an intervention, intense monitoring enables more nuanced understanding of the behavioral processes of uptake and initial adoption. After these first few weeks, however, less intense sampling – perhaps for a random 48-hour period per study week – should capture patterns adequately to understand the long-term adoption of a technology and/or the disadoption of the traditional stoves.

Enumeration of all combustion sources in a household – and at least a rough idea of their use patterns – is essential to properly describe the relationship between stove use and exposure. Substituting one clean-cooking technology for one of multiple traditional stoves used in a household may not result in reduced exposures. This type of enumeration – a combination of survey questions and field worker observations – should be performed seasonally in areas with seasonal weather patterns.

Chapter 5 incorporates many "state of the science" components of household energy and health research to model the potential health benefits of interventions that reduce exposure to HAP. Further research into personal exposures and concentrations will help improve estimates from HAPIT by filling in gaps on integrated-exposure response curves and by helping researchers better understand the sociobehavioral complexities of stove stacking and adoption of clean cooking. Improving HAPIT estimates may enable new avenues for funding intervention programs at different scales, akin to the carbon market – but focused on health. These results-based financing mechanisms, while currently untested, seem a promising way forward to support clean cooking trials and interventions globally.

6.4 Ongoing and future work

The work described in this dissertation could benefit from expansion, replication in additional geographies, and other improvements. The remainder of this section will focus on a number of areas of future research that could benefit ongoing household energy and health research and extend the work described in this volume.

Extending the Stove Use Monitoring System

While much of the work in this dissertation capitalized on leaps in sensor technology and computational power, there exist significant and intriguing possibilities for improving existing sensing platforms to take advantage of widespread cellular networks and low-cost distributed computing. Indeed, for assessments of national programs – such as the Give It Up and Smokeless Village campaigns in India – low-cost stove usage sensors that are programmable (for instance, they turn on once a week and log data), smart (generate summary data), and wireless-enabled (transmit summary data and diagnostics regularly) would greatly simplify and enhance monitoring and evaluation efforts. While this type of technology is currently in use in the United States (US EPA's AirNow system developed by Sonoma Technology, Inc; Aclima's sensing platform) and Europe, its use in the developing world is minimal. Two relevant platforms that are under development are Nexleaf Analytics's (nexleaf.org) Stove Usage Sensor and SweetSense (sweetsensors.com), though both are currently cost-prohibitive for widespread use.

Beyond wireless technologies, an expansion of the family of existing stove use monitoring technologies would assist in instrumenting stoves that are not amenable to measurement by the iButton (described in Chapters 3 and 4). Two technologies currently under development by myself, Berkeley Air Monitoring Group, and EME Systems are the kSUMs, a thermocouple-based SUM, and the irSUM, an infrared thermometer based SUM. The kSUM is a small box (2 inches long, 1.5 inches deep, 1.5 inches wide) with three probes that can be placed close to or directly in open fires to monitor usage. The device can measure up to 1200 ºC, logs data internally to an SD card, and has a battery life of 3-4 weeks.

Little work has been carried out using stove use monitoring data – essentially stove temperatures – to model personal exposures or area concentrations to $PM_{2.5}$. In many study settings, we assume cookstoves relying on solid fuels are the strongest source of emissions and exposures. If this assumption holds, presumably statistical models attempting to explain variability in or predict exposure to $PM_{2.5}$ would be greatly aided by a model term related to a metric from stove use monitors. In a preliminary analysis of exposure data collected concurrently with the SUMs data described in Chapter 4, mixed models were used to explain variability in log-transformed personal exposures to carbon monoxide. The baseline model, which contained a random intercept for household and some household-level fixed effects, explained approximately 40% of the variability in CO concentrations. Inclusion of a value for traditional stove usage led to a model that explained approximately 70% of the variability. While not a surprising finding, it does indicate that including more resolved continuous terms in these types of models may enable us to create strategies to better model personal exposures using a more limited set of measurements.

Finally, work continues on a set of easy-to-use, web-based tools to analyze stove use monitoring data. SUMIT (Stove Use Monitor iButton Tool) analyzes a single file at a time and applies one of three simple algorithms to generate daily use metrics. Development of the second tool, the SUMSarizer, was led by Jeremy Coyle and Daniel Wilson. SUMSarizer ingests large volumes of data and presents a small subset back to the user, who then labels it manually. The labeled data is used to train a machine-learning algorithm, which then proceeds to label all uploaded data and output summary statistics, graphs, and algorithm performance based on cross-validation techniques. Both tools are freely available on the web.

Replicating long-term monitoring in various geographies

Chapters 2 and 4 describe long-term deployment of $PM_{2.5}$ monitors in Guatemala and stove use monitors in India, respectively. While the findings from these studies were instructive for understanding variability in their respective geographies, replication will allow comparison across sites and evaluation of the stability of the relationships described in Chapter 2 and 4. An example of this type of replication – from deployment of $PM_{2.5}$ monitors in Lao for on average 141 days – is included in Appendix D.

A logical extension of long-term monitoring of area concentrations of $PM_{2.5}$ is "extended" monitoring of personal exposure to $PM_{2.5}$. Previously, such an endeavor was nearly impossible due to the burden to participants, who had to either wear an unwieldly but quiet real-time monitor or wear a large, heavy, loud pump attached to a cyclone and filter cassette. However, advances in personal monitoring technology, including the RTI MicroPEM and Enhanced Child Monitor, the Colorado State University Ultrasonic Personal Air Sampler, and the Berkeley Air Monitoring Group Particle and Temperature Sensor +, may enable continuous measurement of exposure to PM for between 7 and 10 days. These types of assessments on a small number of individuals would be instructive in understanding the variability in exposures.

Similarly, replication of long-term monitoring of the usage of both traditional and intervention stoves in numerous geographies could help researchers and implementers understand adoption and disadoption patterns more fully over time. This type of understanding facilitates the results-based financing opportunities enabled by HAPIT: for projects where clean cooking usage remains high and traditional usage remains low, full credit can be awarded; for those where traditional usage is high, attenuated or no credit may be awarded.

Extending and maintaining HAPIT

The aggressive, biyearly update schedule of the Global Burden of Disease poses a significant challenge to maintenance of HAPIT, which relies on up-to-date background disease information to remain policy relevant. The most optimal resolution to this shortcoming would be tighter programmatic integration with IHME datastores via an application programming interface. However, to date, IHME has not provided such an interface to their data.

Beyond background data, there are a number of possible extensions and updates to HAPIT. First, a full exploration of GBD-model uncertainty would help to better bound HAPIT output. However, contextualizing this uncertainty in a policy-relevant form remains troubling. Indeed, trial runs of HAPIT that take into account uncertainty around all parameters yield estimates with very wide bounds and, furthermore, take over an hour to run when optimized for multicore computing. Finding the proper balance between explainability, speed, and accurate depiction of uncertainty remains an ongoing and difficult area of interest.

Second, extension of HAPIT to allow sub-national assessments is vital in countries with wide demographic or geographic variability – like Peru, Mexico, Nepal, and India – where national background disease statistics may not be representative of large population pockets relying on solid fuels for cooking. While implementing this feature is not difficult, finding disaggregated background disease data at the appropriate sub-national scale may be challenging.

Combining monitoring techniques to improve impact assessment

Combining a number of the techniques outlined in this dissertation may improve a study's ability to precisely and accurately assess the impact of a household energy intervention. Assuming an expansive budget for exposure assessment (a sometimes dubious hope), I would thus suggest a multi-tiered approach, beginning with extensive pilot work.

This pilot work would include the types of measurements described in Chapter 2 (long-term monitoring of $PM_{2.5}$) and qualitative work similar to that described in Chapter 3. Additionally, creation and deployment of a rapid survey outlining all potential sources of exposure – including lists of appliances that use dirty fuels in a home, including stoves and lamps; trash-burning behavior, smoking and tobacco use, and proximity to other sources – could help determine the type and variety of exposure sources. These rapid surveys offer quick feedback to which a research team can adapt plans and additionally provide a baseline scenario from which to track changes in cooking habits over time. On the most commonly used stoves (as ascertained by the survey), stove use monitors could be placed to quantify baseline stove use behaviors, though recent evidence indicates a potentially long period of 'reactivity' during which participants use their monitored devices differently due to the presence of the monitor[98]. Finally, any study proposing personal exposure assessment should spend time working within the community to identify a suitable method to place equipment on participants in a comfortable fashion. In Nepal, India, Lao, and Guatemala, we designed a vest with pockets, a conduit for tubing, and a holder for a personal cyclone, CO monitor, and real-time PM monitor in fabric attractive to local participants. The vests were made in each country and designed to distribute weight so that participants could perform their daily activities with minimal intrusion from the equipment. In other locations, backpacks and hip packs have been used with limited success. Regardless, evaluating the optimal form of such an equipment holder during pilot work can prevent delays during the main study.

Providing general suggestions for the "main" portion of a well-funded study is complicated by often diverse primary aims and study questions. This dissertation indicates – at least in the case of stove use (Chapter 4) and kitchen area $PM_{2.5}$ concentration (Chapter 2) monitoring – that there is high variability within and between homes, indicating a need for repeat measures. In both cases, however, it is clear that monitoring continuously for relatively long periods of time (6 months to a year) poses significant logistic and analysis challenges. Smarter strategies informed by long-term monitoring performed during the pilot phase could optimize sampling plans to ensure that studies capture both within and between home variability.

6.5 Summary

This dissertation was built (and titled) around an axiom central to our research group: "you don't get what you expect, you get what you inspect." By using relatively low-cost monitoring technology, this thesis demonstrated that some of the assumptions underlying standard practices in household energy and health research require further investigation. While instructive, the findings described in Chapter 2 and 4 require replication and verification more broadly to see if they hold across study settings. Whether they do or not, more evaluation of the type described here will help the field better understand variability in behavioral patterns that impact exposures and, in turn, help define future measurement and intervention studies. Our findings point toward the need to perform measurement around other areas of uncertainty – such as air exchange rates and variability in personal exposures – to check the validity of current assumptions.

As the field moves toward larger, more rigorous studies – be they clinical trials, such as the US National Institute of Health's multi-center randomized control trial, or our research group's interest in evaluating large clean cooking deployments in India – there will be a significant reliance on sensor technology to track intervention usage and exposure changes over time. These larger evaluations will also require significant pilot work – of the type described in Chapter 3 – to ensure that selected interventions and measurement techniques are appropriate to the communities in which they will be applied. Extensive pilot work as part of these trials may provide some opportunity to evaluate the findings described in this thesis.

The methods and tools evaluated in this dissertation serve dual purposes. They first seek to unpack and validate or refute some of the assumptions common to the household energy and health research enterprise. Second, they seek to find ways to make monitoring and evaluation (A) more accessible for NGOs, governments, and other actors seeking to increase access to clean cooking and (B) more appealing, through the prospects of results-based financing enabled by HAPIT. On the second point, there is much work still to be done to increase the translatability of science into policy-relevant metrics and action.

Appendix A
Abbreviations

AB_{int}	Averted Burden
aDALYs	Averted DALYs
ALRI	Acute lower respiratory infections
ARMS	Air exchange rate monitoring system
BAIRS	Berkeley aerosol information recording system
CO	Carbon monoxide
CO_2	Carbon dioxide
COPD	Chronic obstructive pulmonary disease
COV	Coefficient of variation
CRA	Comparative Risk Assessment
EHS	Environmental Health Sciences
EPA	Environmental Protection Agency
DALYs	Disability-adjust life years
D_{range}	Daily temperature range
GACC	Global Alliance for Clean Cookstoves
GBD-2010	Global Burden of Disease, 2010
GDP	Gross domestic product
HAP	Household air pollution
HAPIT	Household Air Pollution Intervention Tool
$H_{mean\ amb}$	Hourly mean ambient temperature
$H_{sd\ amb}$	Standard deviation of hourly temperature
IERs	Integrated exposure-response
IHD	Ischemic heart disease
IHME	Institute of Health Metrics and Evaluation

INCLEN	International Clinical Epidemiology Network
KAP	Kitchen air pollution
LC	Lung cancer
LMICs	Low and middle-income countries
LPG	Liquefied petroleum gas
MJ	Megajoules
MNRE	Ministry of New and Renewable Energy (Government of India)
NBS	Newborn stove study
NIH	National Institute of Health
PAF	Population attributable fraction
PATS+	Particle and Temperature Sensor +
$PM_{2.5}$	PM with aerodynamic diameter less than 2.5 μm
RCT	Randomized control trial
RESPIRE	Randomized Exposure Study of Pollution Indoors and Respiratory Effect
RMSE	Root mean square error
RR	Relative risk
SD	Standard deviation
SFU	Solid fuel use
SUM	Stove use monitor
SUMS	Stove use monitoring system
UCB-PATS	University of California, Berkeley particle and temperature sensor
UCE	Utilized cooking energy
WHO	World Health Organization
WHO-CHOICE	World Health Organization choosing interventions that are cost-effective
YLDs	Years lost to disability
YLLs	Years of life lost

Appendix B
Supplemental Information for Chapter 2

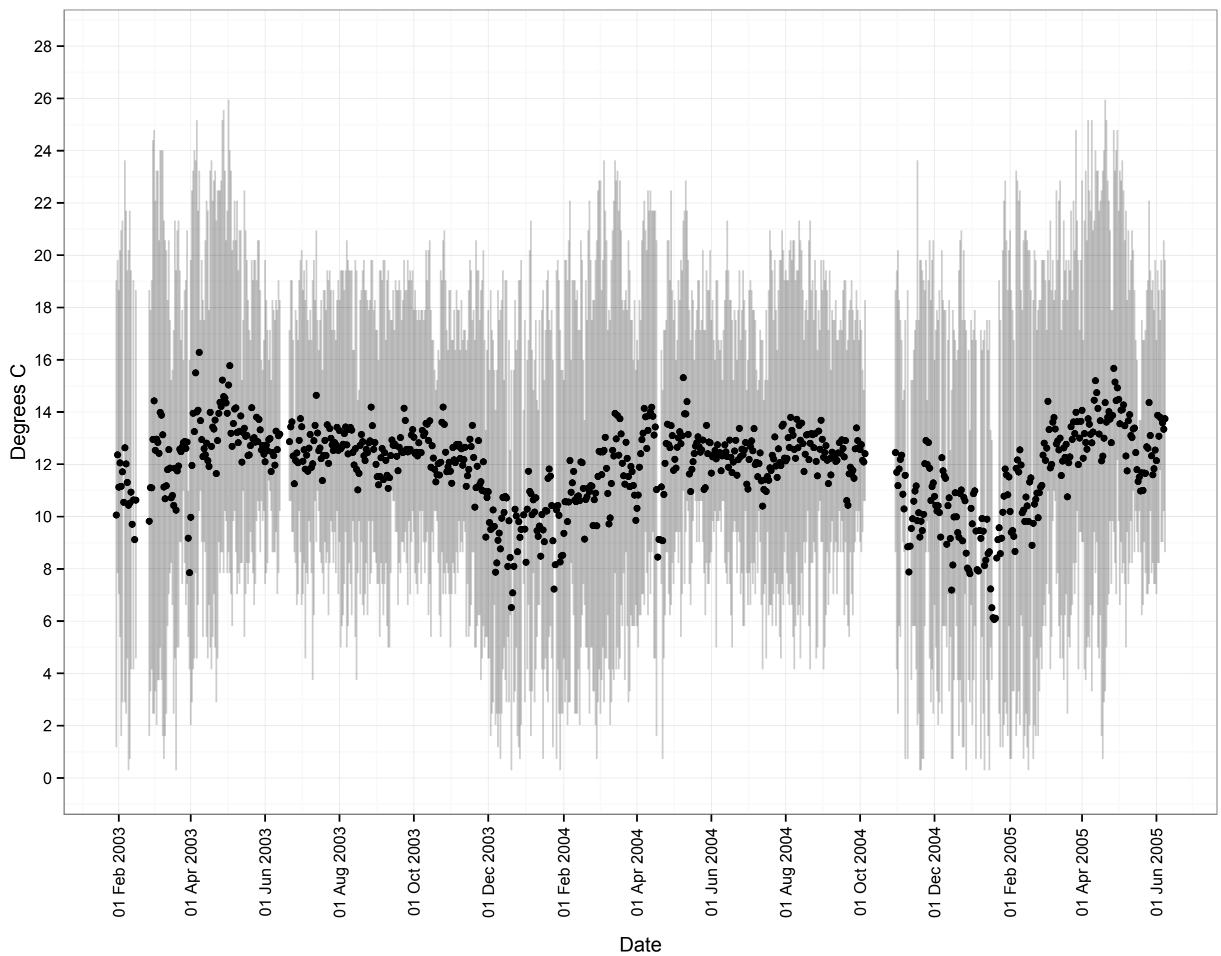

Figure B1 Ambient temperatures at the RESPIRE study headquarters
San Lorenzo, Guatemala (2003 – 2005). The current study occurred between Feb 2004 and Mar 2005. Dots are daily mean temperatures; shading at each point represents the range between the daily minimum and maximum.

Table B1 Unadjusted UCB-PATS concentrations & correction factors

	N	Mean	SD	Min	Median	Max	Start Date	End Date
Open Fire	136	2233	1058	522	2055	5927	7/7/04	12/13/04
Open Fire	134	1107	586	101	972	2874	7/7/04	12/12/04
Open Fire	120	914	489	192	854	3104	2/17/04	7/16/04
Open Fire	215	2690	1498	52	2452	8927	2/24/04	11/22/04
All Open Fire	605	1884	1322	52	1542	8927		
Open Fire Correction	Raw Value * 1.01							
Chimney Stove	154	228	189	62	183	1713	7/7/04	12/31/04
Chimney Stove	215	233	220	65	156	2134	7/7/04	3/21/05
Chimney Stove	333	86	122	50	66	1784	2/17/04	3/21/05
Chimney Stove	327	279	238	68	204	1550	2/17/04	3/21/05
Chimney Stove	1029	199	211	50	133	2134		
Chimney Stove Correction	Raw Value * 0.63							

Table B2 Mean, SD, and range of RMSE estimates

	Mean (μg/m³)		SD (μg/m³)		Min (μg/m³)		Max (μg/m³)	
	OF	Chimney	OF	Chimney	OF	Chimney	OF	Chimney
Randomly Selected Days								
2 Days	774	79	304	30	334	41	1099	109
3 Days	670	63	241	25	262	33	894	87
Random Day by Studymonth	315	56	115	35	186	12	441	109
Random Day by Studyweek	168	26	73	12	93	12	284	45
48 hour period per season	429	48	225	21	204	19	654	64
Consecutive Days								
1	1004	110	427	43	492	50	1510	150
2	774	85	321	34	368	36	1126	111
3	690	76	291	27	324	36	1005	98
4	629	70	270	28	281	30	909	94
5	583	66	253	27	253	26	840	90
6	547	63	241	27	230	24	795	86
7	519	60	233	26	209	22	754	83
8	496	58	223	26	189	21	717	80
9	474	56	213	25	175	19	680	78
10	458	55	206	25	167	19	658	76
14	401	50	186	23	152	17	600	71
21	305	41	120	16	120	16	456	54
28	211	33	59	12	144	14	276	47

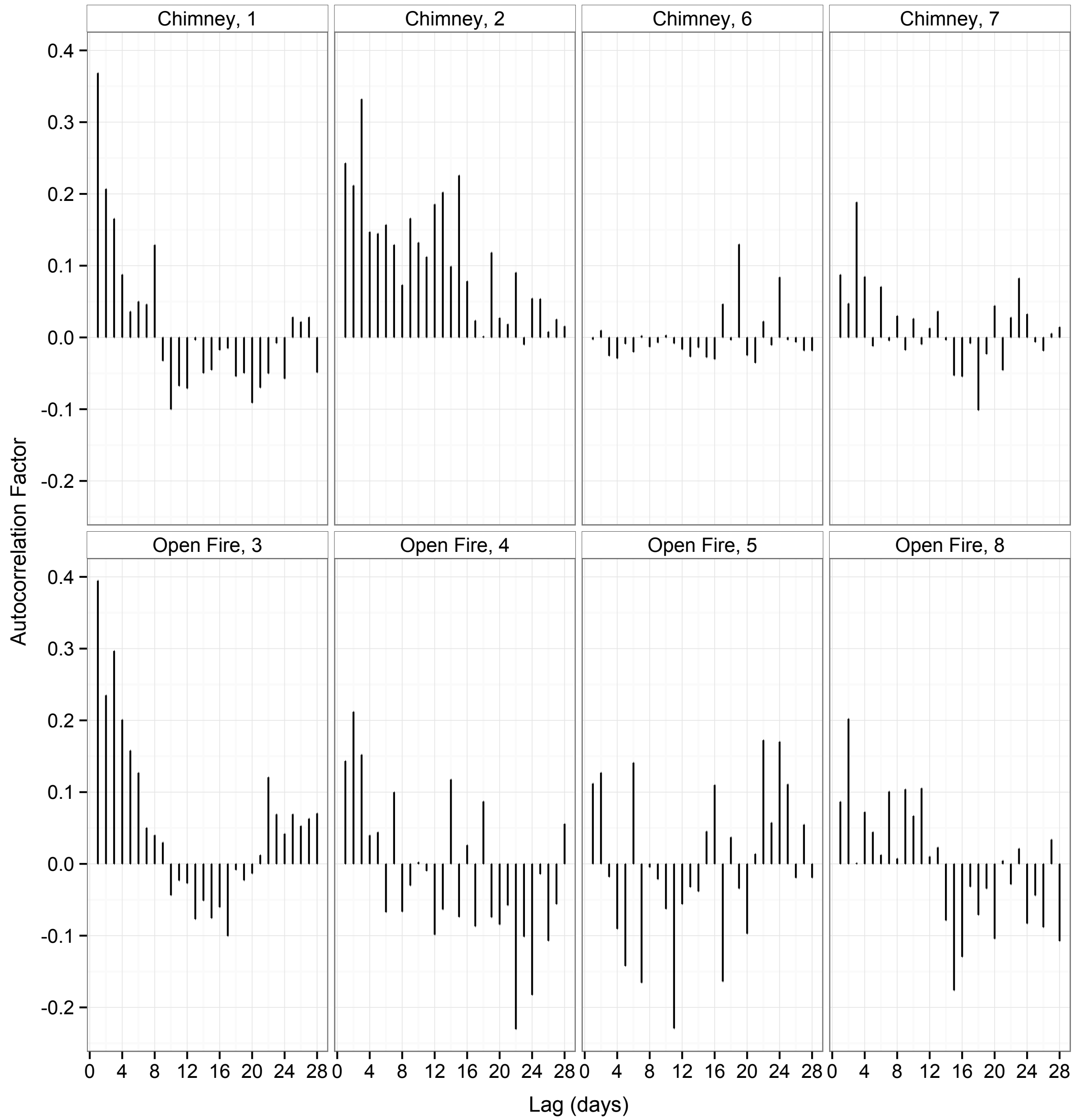

Figure B2 Serial correlation between days of measurements by home

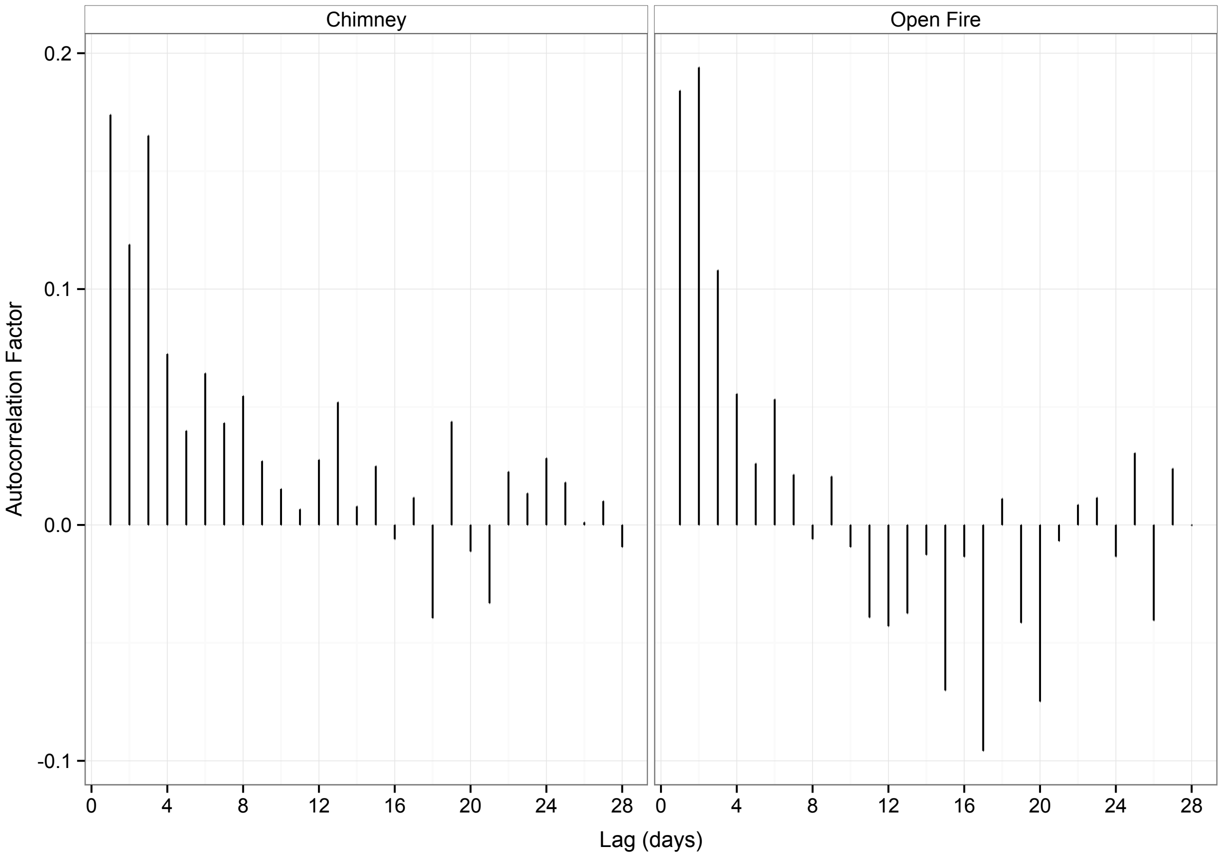

Figure B3 Mean autocorrelation between days of measurements by stove

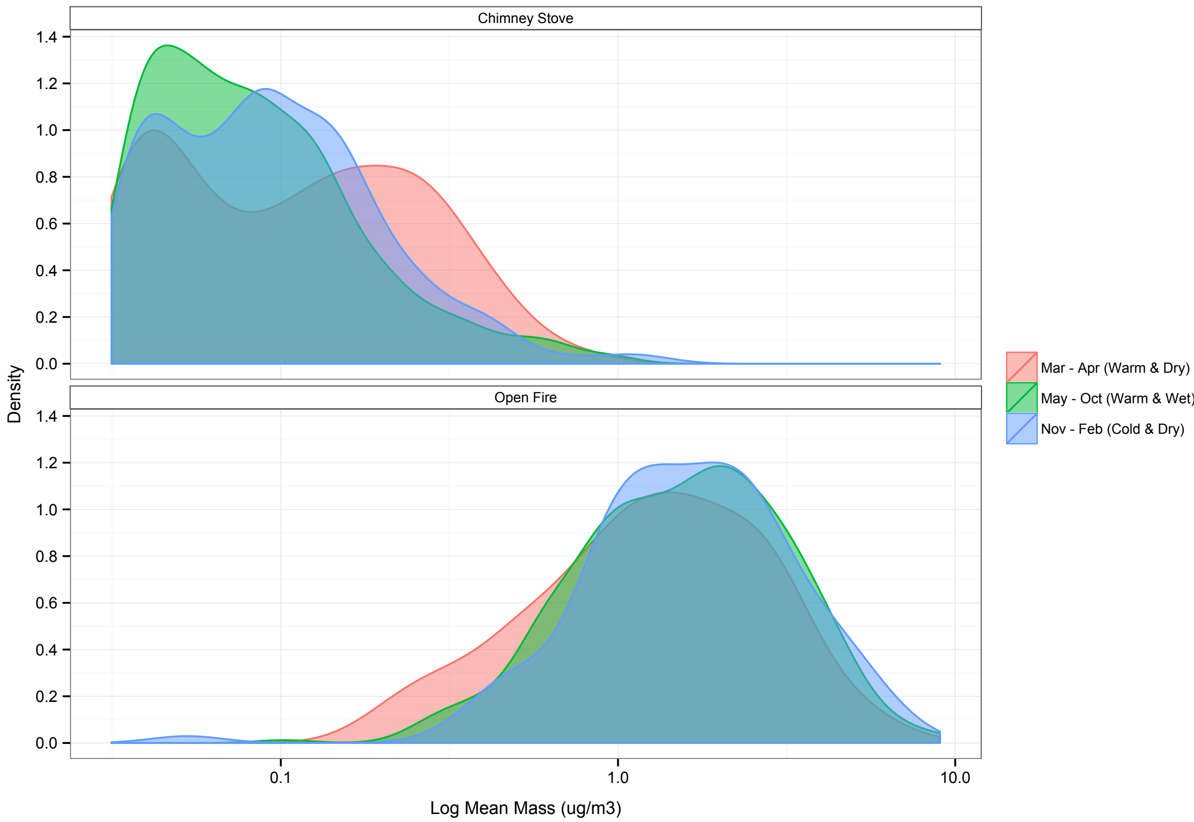

Figure B4 $PM_{2.5}$ distributions by stove type and season
The upper panel is for the chimney stoves; the lower panel is for open fires. Colors correspond with seasons.

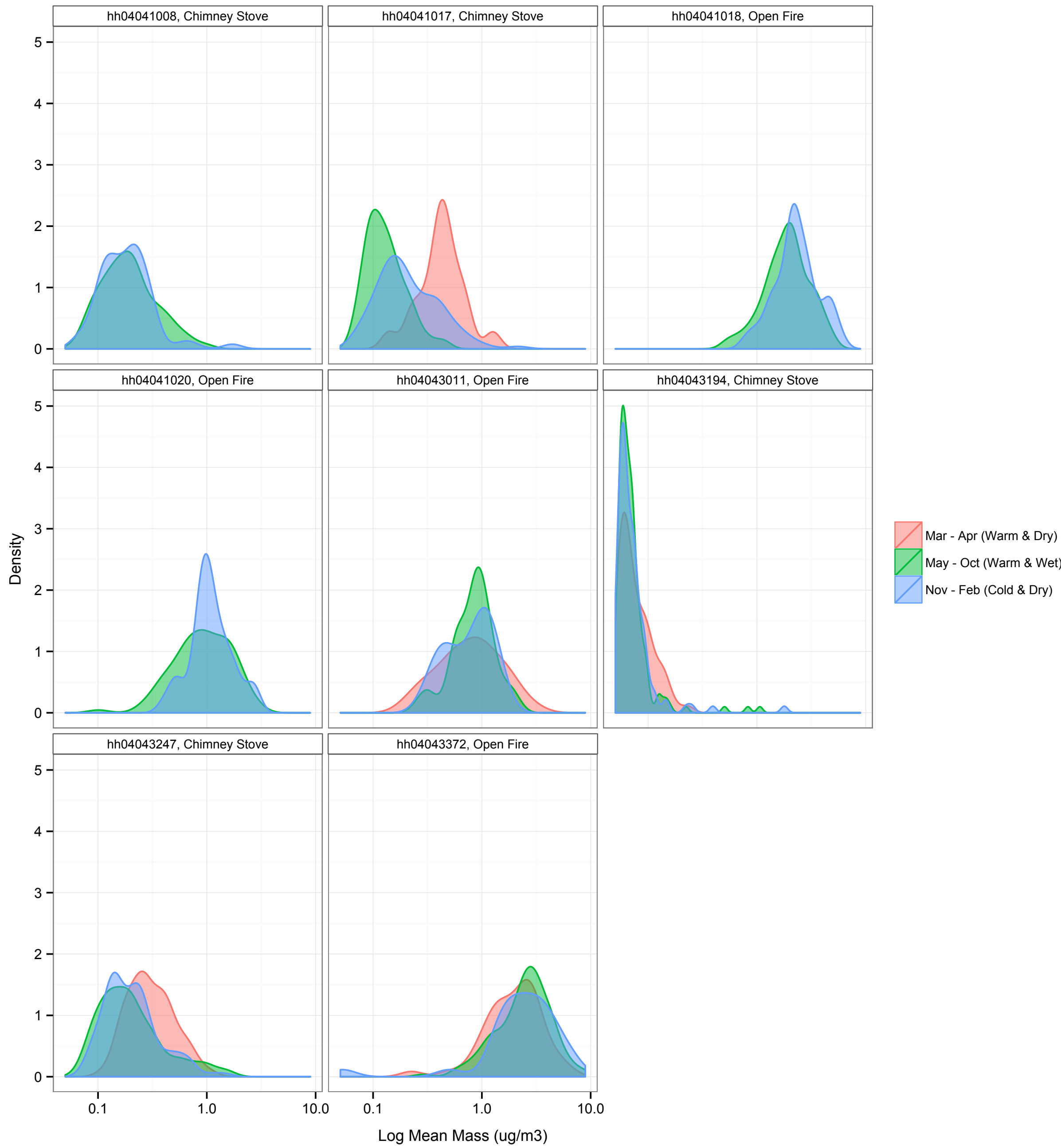

Figure B5 PM$_{2.5}$ distributions by stove type, season and household
Each panel is labeled with a household ID and stove type.

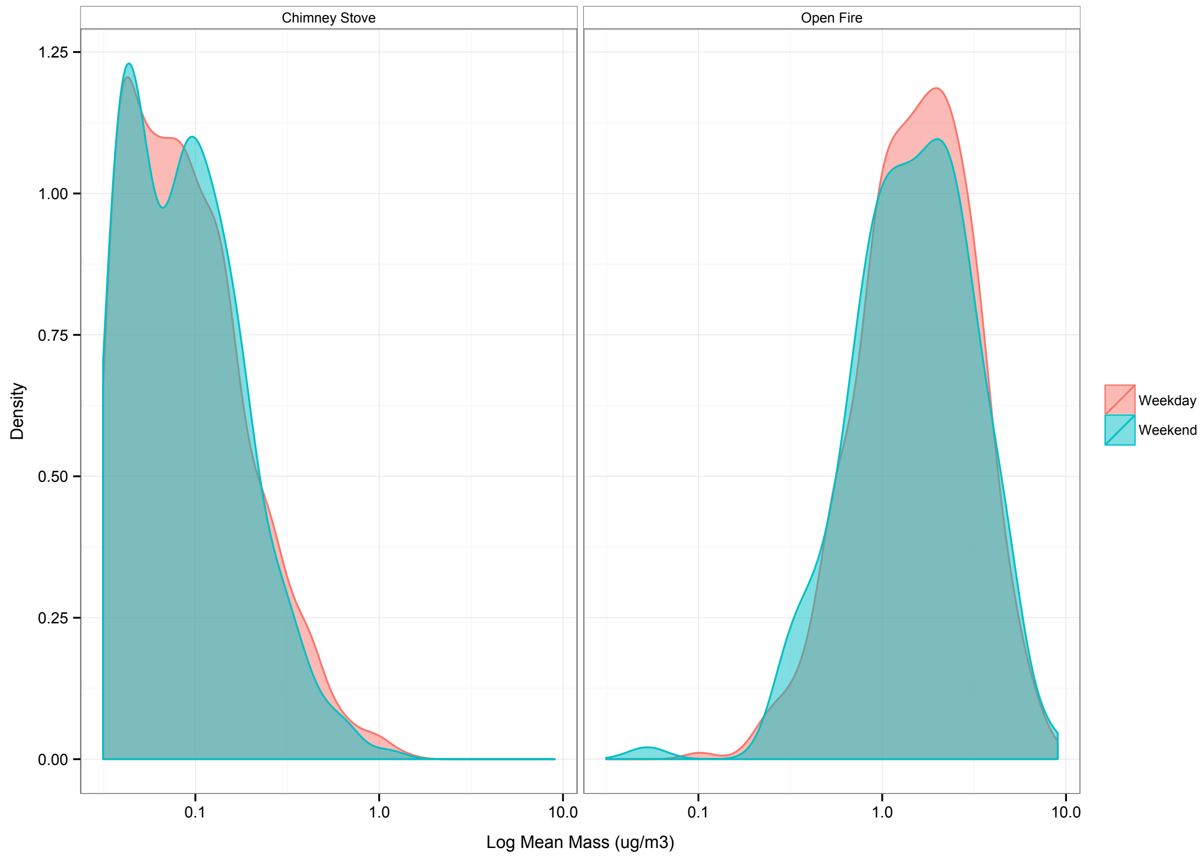

Figure B6 PM$_{2.5}$ distributions by stove type and weekday/weekend
The left panel is for the chimney stoves; the right panel is for open fires. Colors correspond with weekday / weekend.

Table B3 Means and SD of PM$_{2.5}$ exposures and concentrations from global HAP studies

			Kitchen			Personal		
Study	Location	Stove Type	Mean	SD	COV	Mean	SD	COV
McCracken et al, 2007	Guatemala	Open Fire	-	-	-	900	700	0.78
		Plancha	-	-	-	340	490	1.33
Armendariz Arnez et al, 2008	Mexico	Open Fire	1020	790	0.77	240	230	0.96
		Patsari	350	270	0.77	160	130	0.81
Clark et al, 2009	Honduras	Traditional	1002	1089	1.09	198	136	0.69
		Improved	266	240	0.90	74	34	0.46
Van Vliet et al, 2013	Ghana	Mixture	447	410	0.92	129	79	0.61

Table B4 Means and SD of CO exposures and concentrations from global HAP studies

			Kitchen			Personal		
Study	Location	Stove Type	Mean	SD	COV	Mean	SD	COV
Clark et al, 2009	Honduras	Traditional	7.9	11.2	1.42	-	-	-
		Improved	1.8	3.2	1.78	-	-	-
Northcross et al, 2010	Guatemala (mothers)	Open Fire	7.2	6.2	0.85	2.08	1.52	0.73
		Plancha	2.5	4.4	1.76	1.35	1.45	1.07
	Guatemala (child)	Open Fire	7.2	6.2	0.85	0.93	0.57	0.61
		Plancha	2.5	4.4	1.76	0.73	0.58	0.79
Smith et al, 2010	Guatemala (mothers)	Open Fire	8.6	4	0.47	4.8	3.6	0.75
		Plancha	1.1	1.4	1.27	2.2	2.6	1.18
	Guatemala (child)	Open Fire	8.6	4	0.47	2.8	2.5	0.89
		Plancha	1.1	1.4	1.27	1.5	1.9	1.27

Appendix C
Supplemental Information for Chapter 4

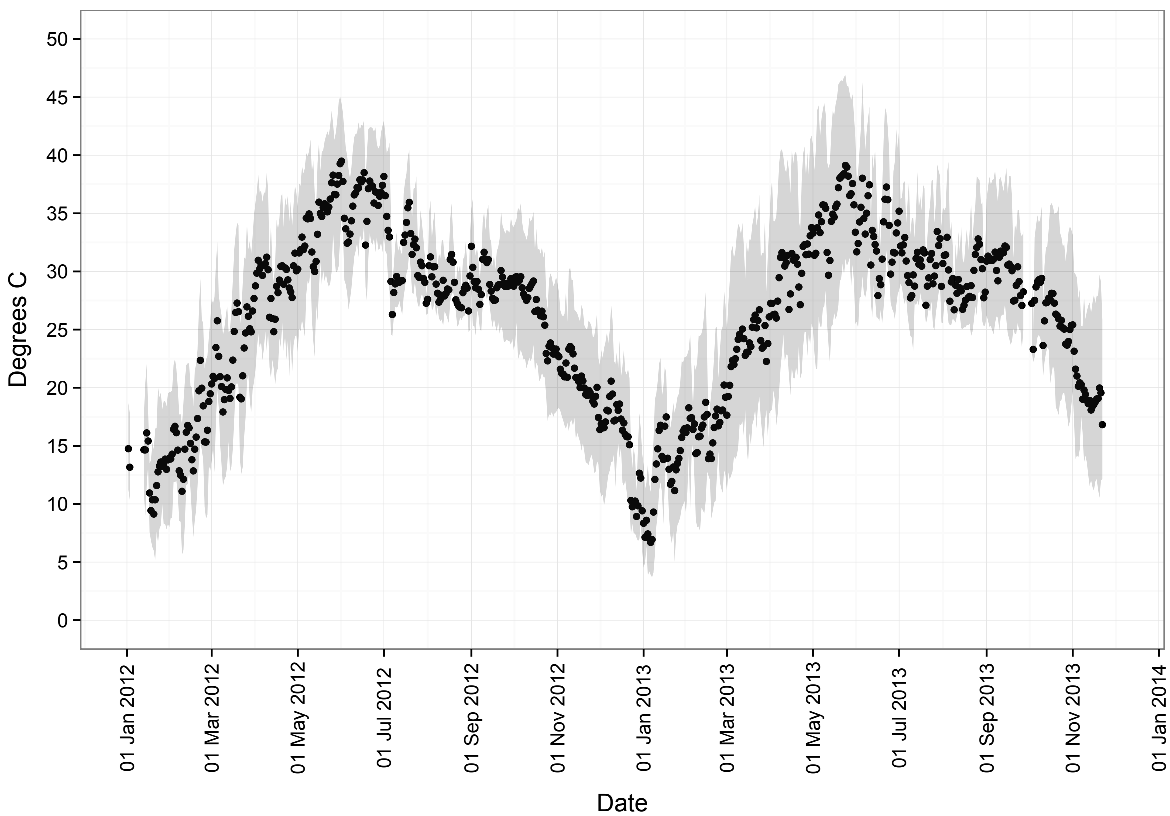

Figure C1 Ambient temperatures in Palwal District, India
Measurements taken at International Clinical Epidemiology Network's headquarters, in Palwal, Haryana, India. Dots are daily mean temperatures; shading at each point represents the range between the daily minimum and maximum.

Counts of stove usage

A commonly reported metric of stove usage is the number of stove use events per day. These raw counts can be considered independently or can be aggregated into "meals" based on knowledge of cultural practices. In the current study, we evaluated the number of discrete events occurring within 40 minutes of each other; for example, two temperature peaks detected at 12:30 and 12:55 would be counted as a single event.

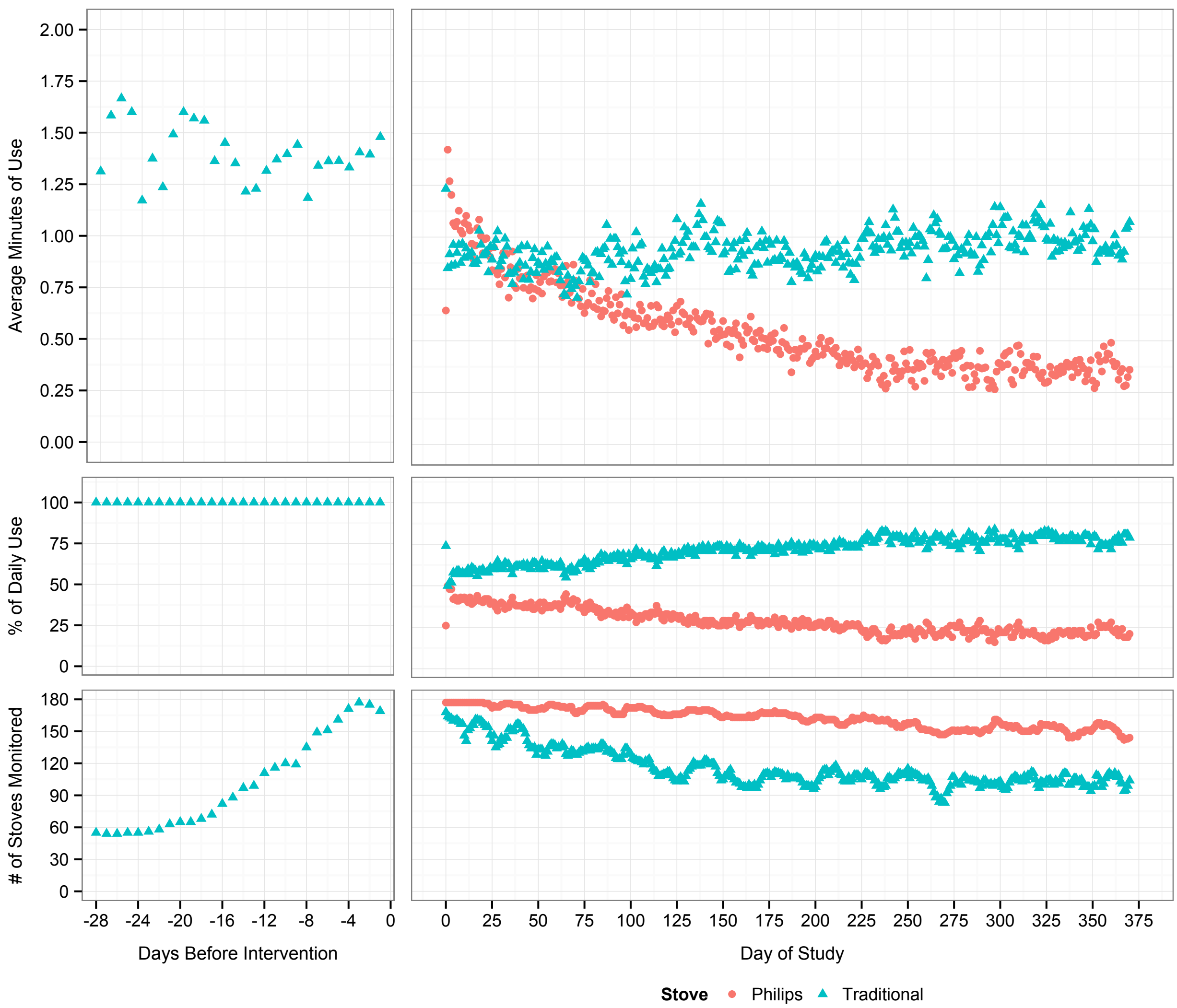

Figure C2 Counts of use of traditional and intervention stoves throughout study
The upper panel depicts daily mean number of uses of monitored stoves by stove type. Day 0 is the day the intervention stove was introduced. The middle panel depicts the percent of stove use events for each stove. The bottom panel depicts the number of stoves monitored per study day.

Trends in event counts over time follow those reported in the main text for durations of use over time. During the initial days and first week after deployment of the Philips, we note use of both stoves, indicating a period during which the Philips was evaluated by households for applicability. Use of the traditional stove remained relatively constant after introduction of the Philips. On average, prior to the introduction of the Philips, traditional stoves were used 1.4 times (SD = 0.8) per day. After introduction of the intervention, average usage of the traditional stoves decreased to 1 time per day; the Philips was used 0.6 times per day. While trends in use of the traditional stove were relatively stable post-intervention, Philips use decreased linearly. While event counts are useful for tracking adoption, they fail to capture duration of use, which we believe to be a more useful metric.

Restricted analysis

Due to missing data from both the traditional and intervention stoves, we performed the same analysis described in the main text on days for which we had data on both the traditional and intervention stoves (n = 49,279 days). Trends mirrored those reported in the main text and are summarized in Table C1 and Figure C2.

Table C1 Study means of post-intervention use from the restricted and full analyses

	Mean (SD) (minutes, restricted analysis)	Mean (SD) (minutes, full analysis)
Traditional	145.7 (134.1)	143.9 (133.6)
Philips	64.87 (88.3)	60.0 (86.8)

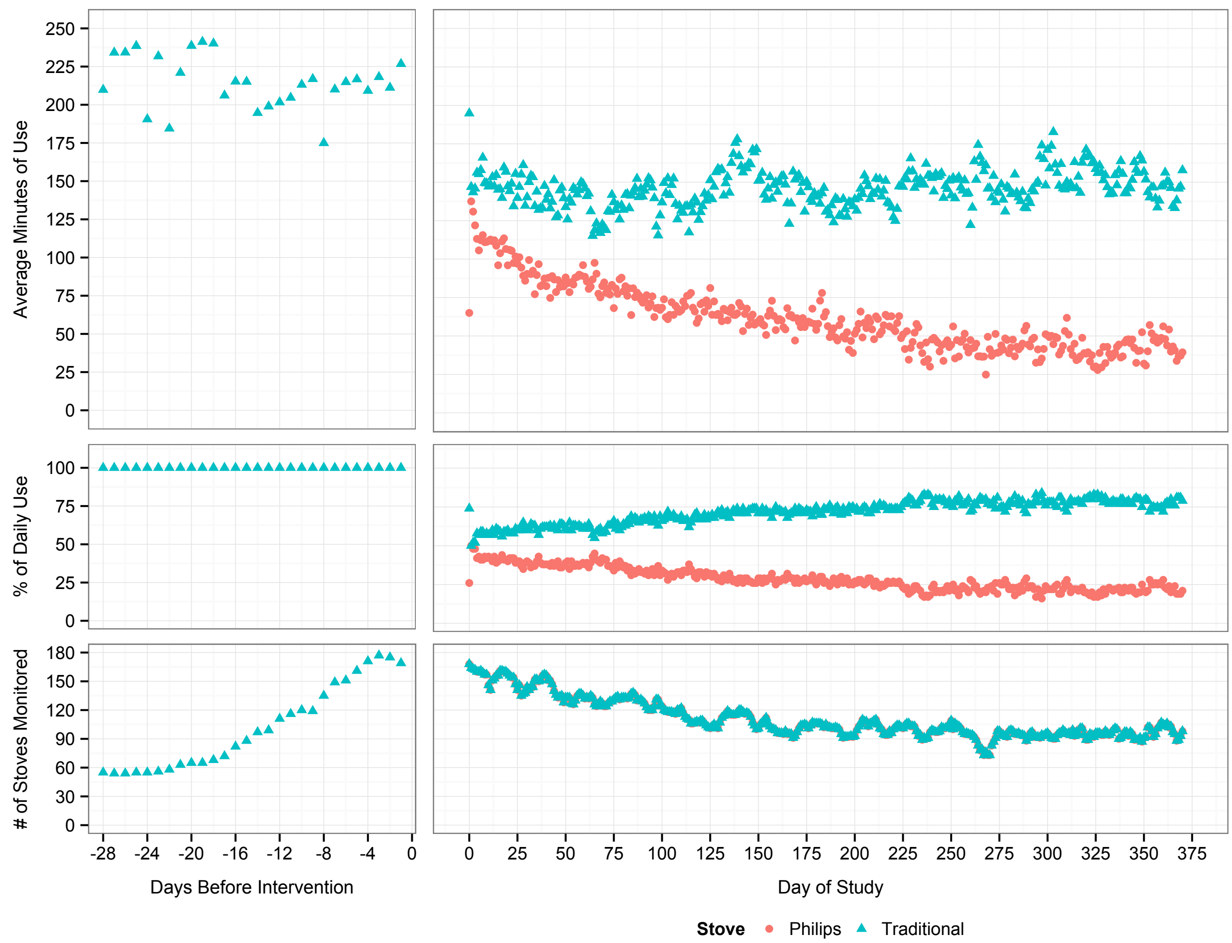

Figure C3 Stoves use throughout study on days with valid data for both stoves
The upper panel depicts daily mean usage of monitored stoves by stove type. Day 0 is the day the intervention stove was introduced. The middle panel depicts the percent of stove use time each stove was used. The bottom panel depicts the number of stoves monitored per study day.

Trends for utilized cooking energy (UCE) in this restricted analysis followed patterns shown in the main text and are depicted in Figure C3 and Table C2.

Table C2 Study means of post-intervention UCE from the restricted and full analyses

	Mean (SD) (MJ, restricted analysis)	Mean (SD) (MJ, full analysis)
Traditional	10.7 (0.9)	10.6 (0.9)
Philips	6.1 (2.1)	5.9 (2.0)
Total	16.8 (2.1)	16.5 (2.0)

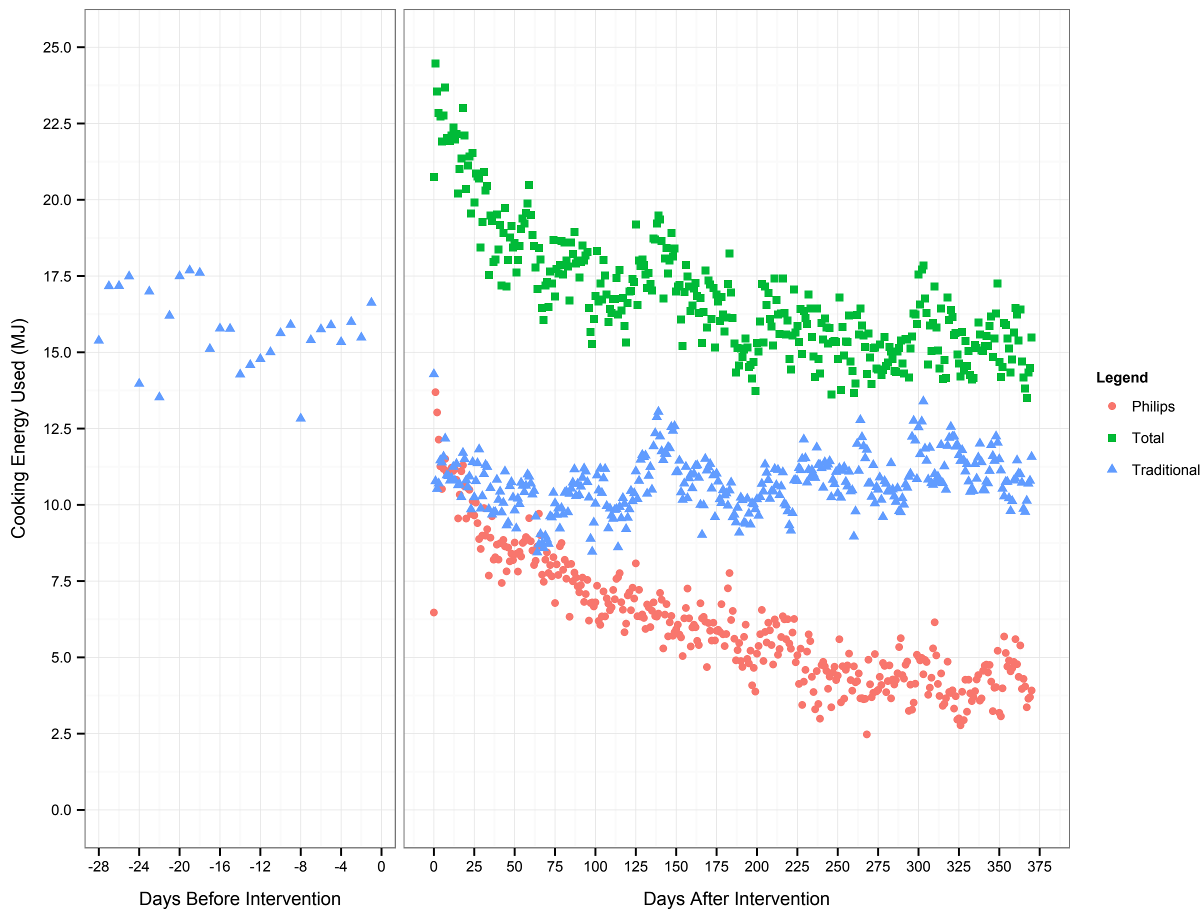

Figure C4 Utilized cooking energy in megajoules throughout intervention for the restricted dataset *The utilized cooking energy is presented separately for the traditional and intervention stoves (blue triangles and red squares, respectively) and pre and post-intervention periods. The total energy use is presented in green squares.*

Table C3 Daily usage duration means and intraclass correlation coefficients

	Mean (minutes) per day (95% Confidence interval)	Intraclass Correlation (95% CI)
Traditional		
Pre-intervention[a]	209.2 (205.4 to 212.9)	0.25 (0.20 to 0.30)
Post-intervention[b]	143.9 (142.7 to 145.2)	0.35 (0.30 to 0.41)
Philips[c]	60.0 (59.3 to 60.7)	0.22 (0.18 to 0.25)

95% confidence interval in parentheses
[a] 2958 stove days from 177 homes
[b] 44448 stove days from 177 homes
[c] 63433 stove days from 177 homes

Optimizing SUMs sampling strategies

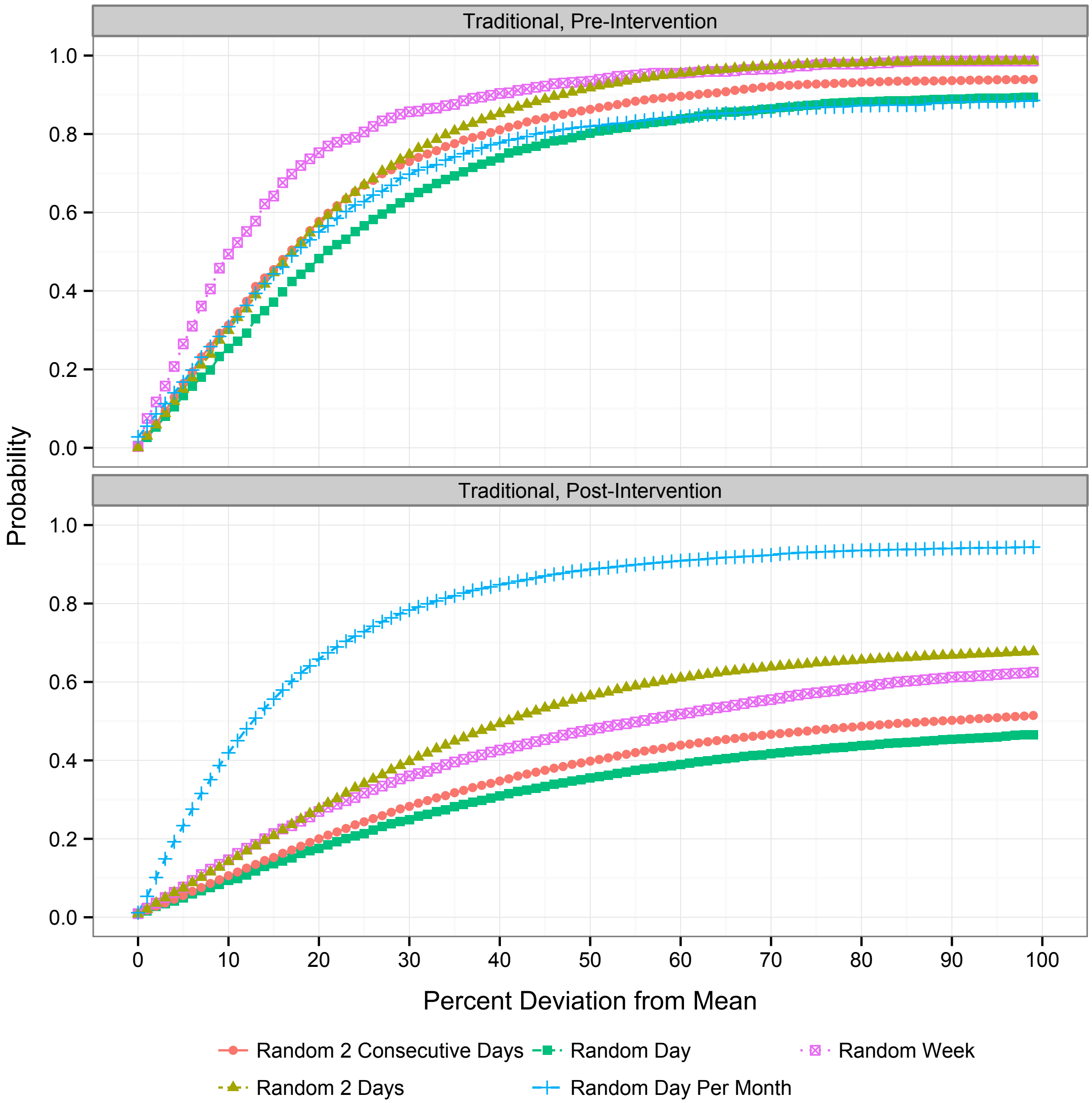

Figure C5 Optimizing measurement strategies for SUMs sampling
The upper panel shows the precision of various short-term measures of use of the traditional stove prior to introduction of the intervention; the bottom panel shows the precision of short-term measures of use of the traditional after introduction of the intervention.

Table C4 Probability of obtaining usage estimates within 20% of study mean

	Pre-Intervention Traditional Stove	**Post-Intervention** Traditional Stove
Single Day	0.48	0.18
Two Consecutive Days	0.58	0.20
Two Non-consecutive Days	0.57	0.28
Random Week	0.75	0.27
One Day per Study Month	0.55	0.66

Maintenance and repair of Philips stoves

Field staff visited homes every two weeks to download data from SUMs. During these visits, they observed stove performance and recorded findings. A total of 1387 stove observation visits were recorded. Between visits, participants could call field staff to report issues with the Philips or bring malfunctioning units to study headquarters. Study staff attempted to perform repairs on broken stoves; if they were unable to fix the stove, trained technicians were hired. A small supply of replacement stoves was available to supply homes with continual service throughout the study period.

Stove failures were categorized into 9 categories: battery failures, printed circuit board (PCB) failures, charger failures, knob failures, cracked or shattered plastic base, fan failures, internal plates cracked, broken, or collapsed; top of stove corroded, and other. Of the stoves distributed, 142 had at least one failure that resulted in a repair. The mean time to first failure was 171 days. Failure types are summarized in Figures C4 and Table C3.

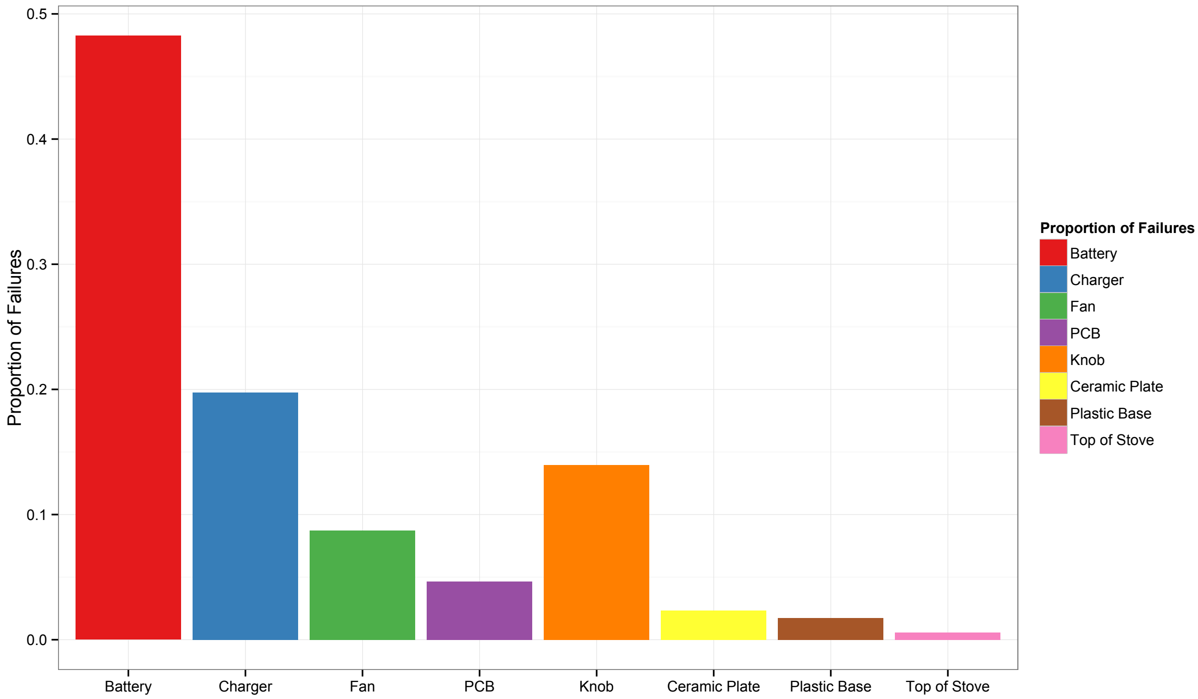

Figure C6 Counts of first failures of Philips stoves

Table C5 Summary of failures observed during fieldworker visual inspection of Philips stoves.

Fuel Chamber (cracked)	**6**
Stove Body	**26**
Broken	17
Dented	9
Knob	**48**
Broken	11
Missing	1
Jammed	36
Battery & Charger	**75**
Not charging	72
Missing	3
Fan Not Working	**32**

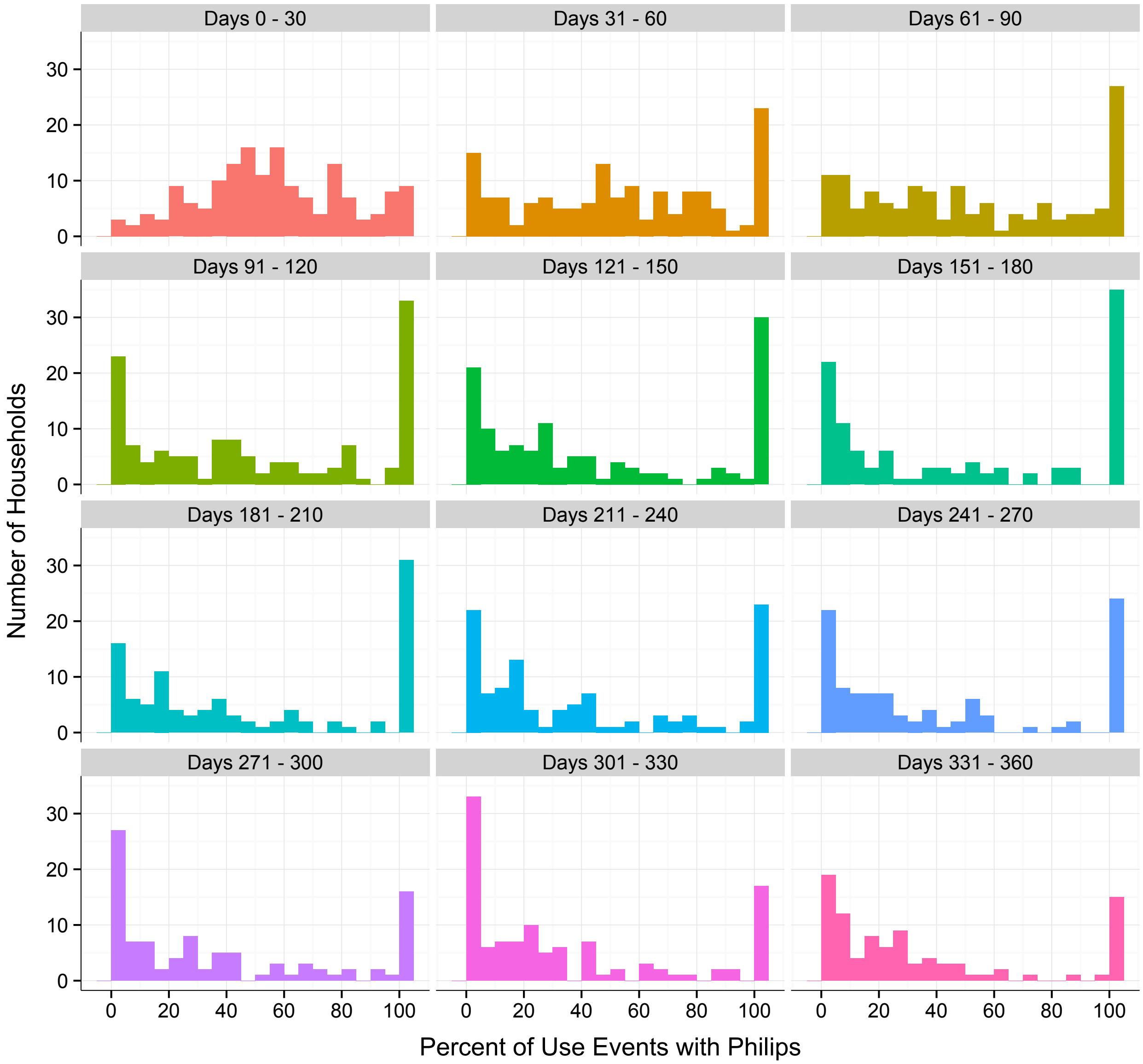

Figure C7 Percent of use events with Philips
Panels are 30 study days in length, denoted in the topmost gray area. Homes with no cooking are not included. Bars indicate the number of households using a stove for a corresponding period of time.

SUMs field performance
Field workers downloaded data from stoves 9131 times during approximately 4737 household visits. On average, each of the 200 households was visited 22.8 times. Of the 9131 downloads, 83% yielded data (n = 7613). Figure C8 depicts the frequency of data retrieval failures by cause, including an inability to access the stove (Door Locked), damage to the SUMs from heat or water resulting in an ability to download data; data errors due to sensor malfunctioning, lost or misplaced SUMs, or SUMs that had split apart or burst due to exposure to excess heat.

Data loss impacted the traditional stoves more significantly than the intervention stoves. Traditional stoves varied widely in construction; in some households, placement of the SUMs in the 'standard' location resulted in either over-heating or exposure to water from cooking. We believe the wave-like pattern present in the post-intervention traditional homes (Main text, Figure 4.3, bottom panel) occurred because of detection of SUMs failures during household visits, which occurred in clusters at two week intervals.

We approximated the total number of data points that should have been collected during the study by subtracting the initial data collection date from the final data collection date and multiplying the number obtained in days by 144 (the number of data points collected per day). We collected 93% and 67% of the expected data for the Philips and traditional stoves, respectively.

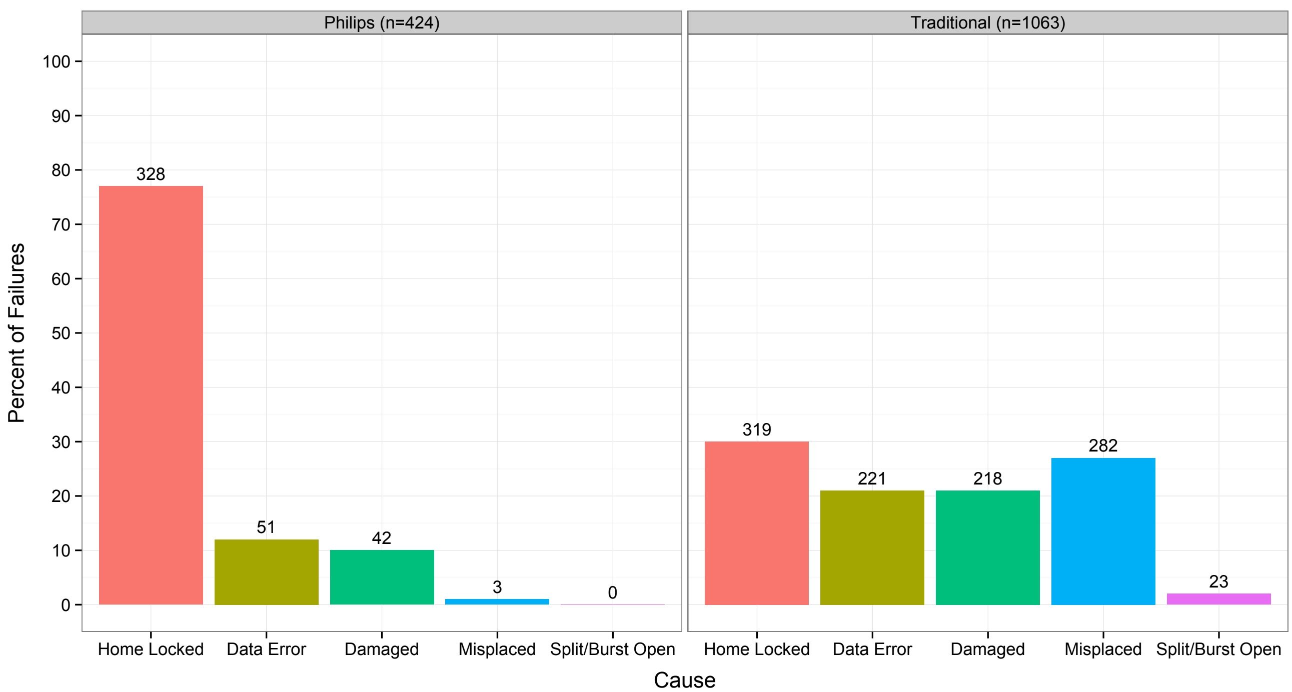

Figure C8 Stove Use Monitors data loss by cause
Numbers above the bars indicate the counts per failure type.

Appendix D

Long-term monitoring of $PM_{2.5}$ concentrations in Laos to evaluate household-level variability

Overview

$PM_{2.5}$ was monitored continuously to better understand the coefficient of variation (CoV), a unitless metric of variability and dispersion, prior to designing the main before-and-after study. The CoV is calculated by dividing the standard deviation by the mean. The larger the CoV, the more highly variable the data. Ideally, the CoV would be evaluated prior to the start of any household energy and health project; in this study, $PM_{2.5}$ measurements began before the project, but continued throughout the deployment of the intervention.

Methods

In four households in Laos, we evaluated the concentrations of $PM_{2.5}$ in the primary kitchen for approximately 141 days (range 128 – 159 days). Sampling took place between mid-August 2014 and February 2015. Kitchen concentrations were recorded every minute using real time $PM_{2.5}$ data-logging monitors that utilize a light-scattering sensor (UCB-PATS). The UCB-PATS were placed in the participant's kitchen at approximately 1.0 meter from the stove and 1.5 meters above the floor, a standardized location meant to represent the approximate breathing zone of a woman standing near the stove. The households selected for this study were not participants in the main study.

From the collected data, we retained days of data that contained at least 1296 data points (90% of the expected 1440 daily datapoints). We calculated the unadjusted daily mean and standard deviation of the $PM_{2.5}$ concentration in each home. We then calculated the CoV of samples of 2, 3, 4, 5, 7, 10, 14, 21, and 28 days to evaluate how the CoV changed as the number of consecutive sampling days increased. We additionally compared the CoV of measurements taken in households during the main study to (1) CoVs calculated over the entire long-term monitoring period for long-term monitoring households and (2) to CoVs calculated during main-study sampling dates only in long-term monitoring households.

Findings

COVs declined steadily with increasing consecutive days of sampling. Figure D1 depicts the decline in COVs for every evaluated period; all households experienced similar declines (described numerically in Table D1). The COV is substantially higher in household 4 than in the remaining 3, though the reason for this difference is unknown. Figure D2 focuses on measurements of lengths ranging between 2 and 7 days, the most viable for household air pollution assessments. For all households, the COV decreases with increasing measurement days; the rate of decline begins to flatten out after 5 days of measurement.

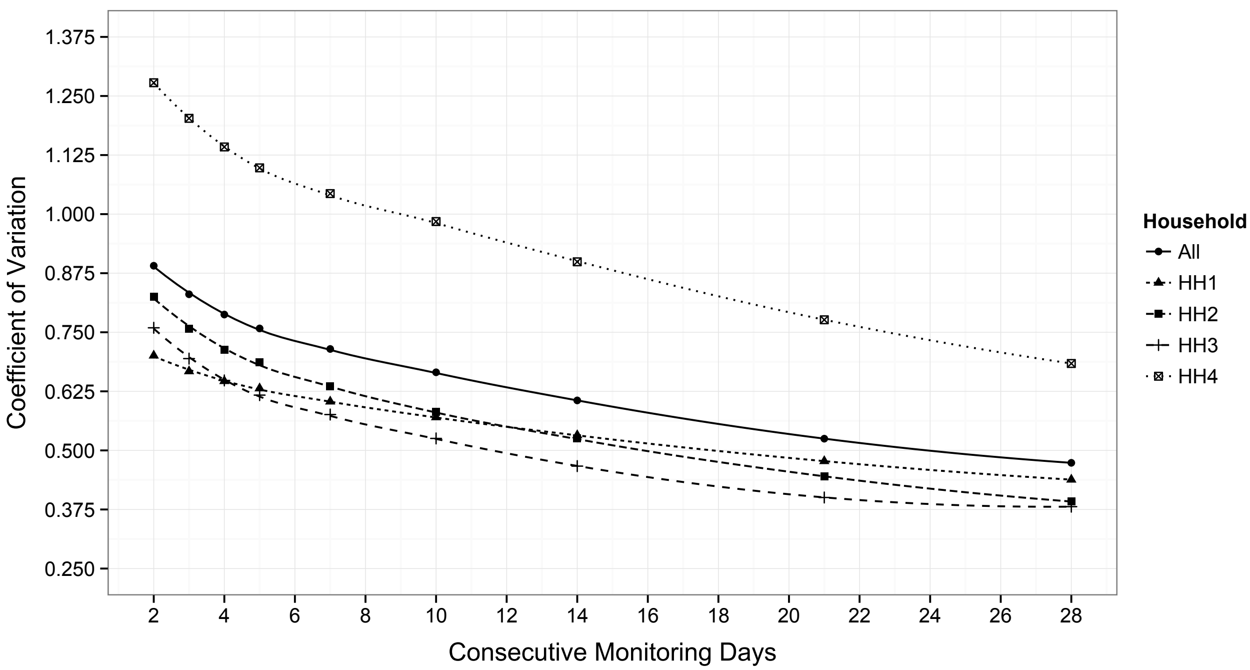

Figure D1 The reduction in COV as the number of monitoring days increases
Each household in the study is represented separately with a unique line-type and bullet. The solid line with circular bullets is the mean of the COV for all households. The COV decreases as the number of sampling days increases.

During the main study, at least 3 consecutive days of valid UCB data were collected in 64 homes during the before period and in 60 homes during the after period. For each period, we calculated the mean COV over these 3 or 4 day samples. During the before intervention period, the average COV was 0.34 (range 0.07 – 0.91); during the after period, it decreased to 0.30 (range 0.03 – 0.96); this contrasts with the COV calculated during the long-term monitoring, which for periods of similar length (4 days) was 0.79 (range 0.65 – 1.14).

Table D1 COVs for increasing monitoring days in Lao

	Consecutive Monitoring Days								
	2	3	4	5	7	10	14	21	28
All	0.89	0.83	0.79	0.76	0.72	0.67	0.61	0.52	0.47
HH1	0.70	0.67	0.65	0.63	0.60	0.57	0.53	0.48	0.44
HH2	0.82	0.76	0.71	0.69	0.64	0.58	0.53	0.45	0.39
HH3	0.76	0.69	0.65	0.62	0.58	0.53	0.47	0.40	0.38
HH4	1.28	1.20	1.14	1.10	1.05	0.98	0.90	0.78	0.68

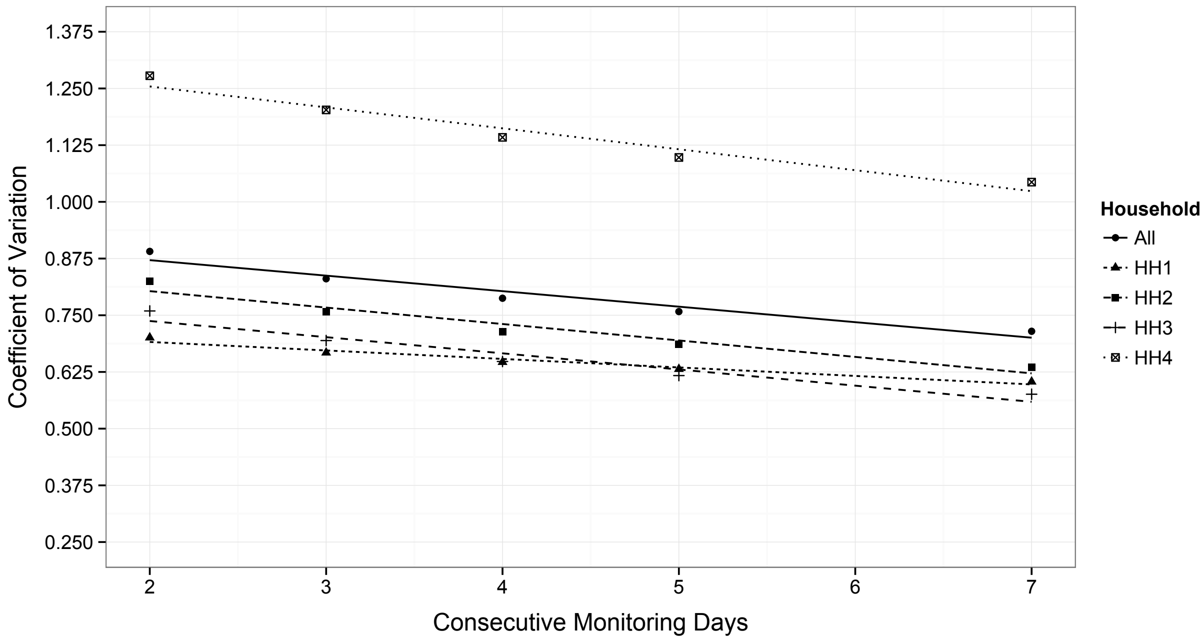

Figure D2 The reduction in the coefficient of variation for 2 to 7 days.
Each household in the study is represented separately with a unique line-type and bullet. The solid line with circular bullets is the mean of the COV for all households. The COV decreases as the number of sampling days increases.

The discrepancy between the COV calculated during the main study and the long-term monitoring substudy may be due to a number of factors. First, the village where long-term monitoring was performed was not one of the study villages. Second, the discrepancy could reflect true month-to-month variability, which is borne out to some degree by the long-term data (Figure 2). When the the long-term monitoring COVs are calculated over the same period as the before monitoring (mid-December 2014 – early-January 2015), the discrepancy between COVs is reduced. During the before period in the long-term monitoring households, the average COV was 0.59 (range 0.19 – 0.97). If household 4 is excluded (its COV is over double the next closest household), the mean COV is 0.29 (range 0.19 – 0.41). A similar comparison for the post-intervention period is not reported due to probable changes in cooking due to introduction of the intervention. Finally, the comparison during the post-intervention period is perhaps not a reliable indicator of actual conditions, given the changing dynamics of the kitchen during the introduction of an intervention.

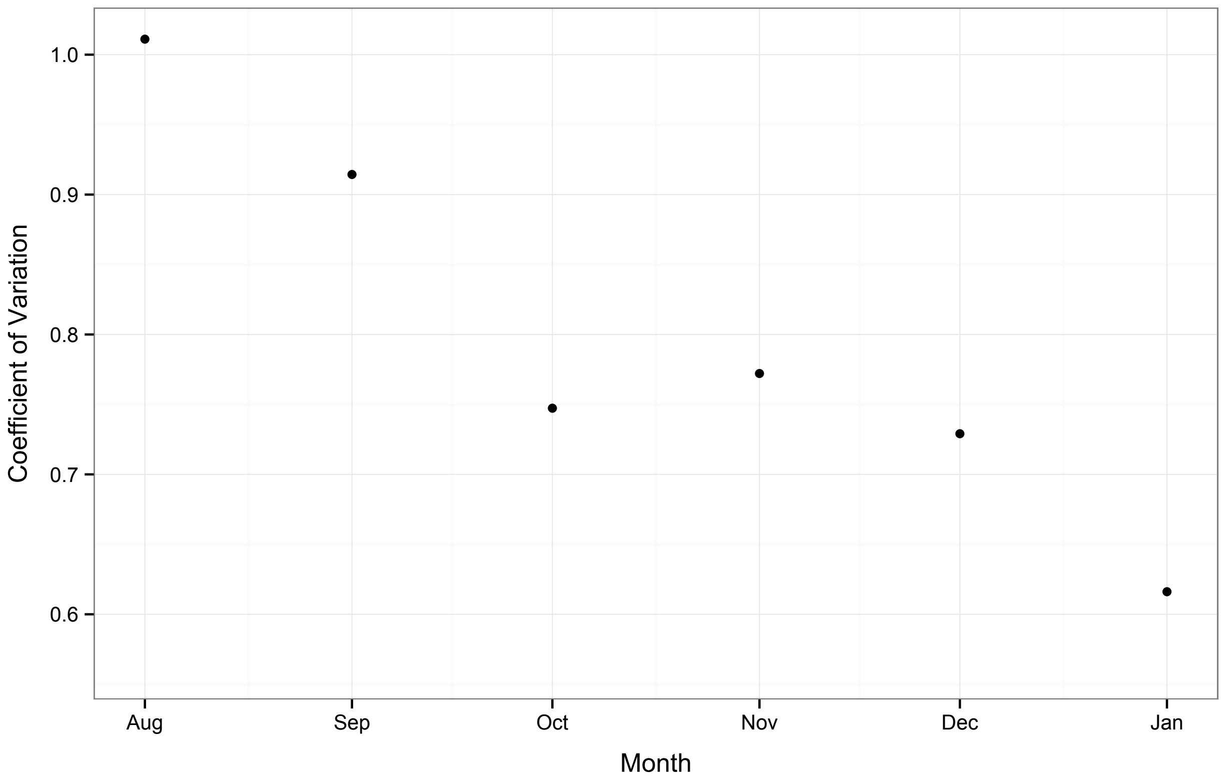

Figure D2 Changes in COV by month in Lao

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