ABSTRACT

Title of Dissertation: HOUSEHOLD ENERGY USE, INDOOR AIR POLLUTION, AND HEALTH IMPACTS IN INIDA: A WELFARE ANALYSIS

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This dissertation develops a unified analytical framework to understand the relationships among household energy use, indoor air pollution (IAP), and health impacts and enables policy-makers to analyze welfare effects of various interventions.

This unified analytical framework includes four interlinked modules. Module 1 studies the determinants of IAP and constructs an IAP index to predict typical IAP exposure. Module 2 analyzes the impacts of IAP exposure on health, including both self-reported respiratory symptoms and physician-measured spirometry indicators. Module 3 uses a novel approach to model household behavior regarding energy technology choices based on utility maximizing behavior. Households are assumed to choose a cooking energy technology based on its attributes: cooking cost, convenience, and cleanliness. Household valuation of these attributes depends on household characteristics. Then based on the household utility function estimated from Module 3, Module 4 evaluates welfare change from various policy interventions.

Empirical estimation relies primarily on two surveys recently conducted in India: a social science and environmental health survey entitled Health, Environment, and Economic Development and a multi-topic national representative sample survey called

the India Human Development Survey. The two surveys were fielded between late 2004 and early 2005 and contain uniquely rich information on household energy use, indoor air pollution levels, and health indicators.

This dissertation provides quantitative evidence that IAP has significant health impacts comparable to smoking. Based on analysis of IAP impacts on spirometry indicators, the evidence suggests that IAP has major impacts on restrictive lung disease rather than obstructive lung disease. These results explain why certain diseases are more highly associated with IAP exposure. Considering that traditional biomass will likely continue to be the most popular cooking fuel in rural areas of India in the near future, and that households can achieve considerable welfare gains from improvement in stoves and kitchen ventilation, the analysis suggests that the Indian government should consider reviving the improved stove program with a new advanced stove strategy coupled with conducting advocacy campaigns on how to improve kitchen ventilation. The analysis suggests small overall welfare effects of the pending phasing out of LPG subsidies.

HOUSEHOLD ENERGY USE, INDOOR AIR POLLUTION, AND HEALTH IMPACTS IN INIDA: A WELFARE ANALYSIS

by

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DEDICATION

To my parents, my husband, and my daughter

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Chapter 1. Introduction

Burning biomass in traditional stoves emits smoke containing large quantities of particulate matter and gaseous pollutants, with serious health consequences for the exposed population. Global estimates show that about 2.5 million deaths each year result from indoor exposure to particulate matter in rural and urban areas in developing countries, representing 4-5% of the 50-60 million global deaths that occur annually (Bruce, et al., 2002). The situation is particularly bad in India. The World Health Organization estimates that exposure to indoor air pollution (IAP) causes about 500,000 premature deaths and 500 million incidences of illness among women and children in India each year. This amounts to 30 percent of the global disease burden from this risk factor in the developing world and makes IAP one of the top preventable health risks in India (Energy Sector Management Assistant Program, 2002).

Switching to clean fuel has been identified as the most effective way of reducing IAP. However, the progress of adopting modern energy in rural India has been slow. Household use of traditional biomass fuels including firewood, wood chips, crop residue, and dung cakes are still widespread in rural India. The recent national representative survey, the India Human Development Survey (IHDS) 2004-2005, shows that 90% of rural households and 40% of urban households still rely on biomass as their primary cooking fuel. Half of rural households still use very inefficient cooking fuels such as dung cake and crop residue. The improved chulha (stove) has been considered to be an effective alternative to reduce IAP. However, only 5% of Indian people are using the improved chulha as their primary stove.

Research Questions

Why do people use household energy technologies that can make them sick or even cause death? My dissertation uses recent household survey data from India to explore this puzzle through quantifying the relationships among household energy use, indoor air pollution, and health impacts. Based on these relationships, my dissertation will develop a model of household behavior to evaluate welfare changes from a variety of policy interventions such as promoting improved stoves, improving kitchen ventilation, and phasing out LPG subsidies. More specifically, I answer the following questions.

1. Which factors determine IAP concentrations and what are their relative contributions? These factors include energy technology (the stove-fuel combination), housing characteristics, and cooking practice.
2. What is the quantitative relationship between exposure to IAP and the incidence of disease?
3. What factors affect households' decisions on the energy technology choice? What policy interventions might be implemented to influence the choices?
4. How can the welfare effects from various interventions be measured? What are the welfare effects of alternative interventions?

Problem Motivation

IAP has gained attention mainly due to its health impacts, including respiratory diseases in particular. Respiratory diseases have consistently been among the most prevalent diseases of developing countries (WHO, 2002). However, no reference to the role of air pollution in the incidence of diseases was made in the medical community until early in the 20th century (Ezzati and Kammen, 2002, and Smith, et al. 2000). Air pollution was first considered as a major cause for respiratory diseases after some dramatic episodes of outdoor air pollution. For example, the Big Smoke during the 5-8 December, 1952, in London, which was due mainly to smoke from coal burning household stoves, killed about 4,000 people during the first three weeks of December—most of whom were very young or elderly, or had pre-existing respiratory problems (MOH, 1954). Another 8,000 died in the weeks and months that followed (Pearce, 1992). As shown in Figure 1-1, deaths per day closely followed smoke concentrations, which imply a direct linkage between the two.

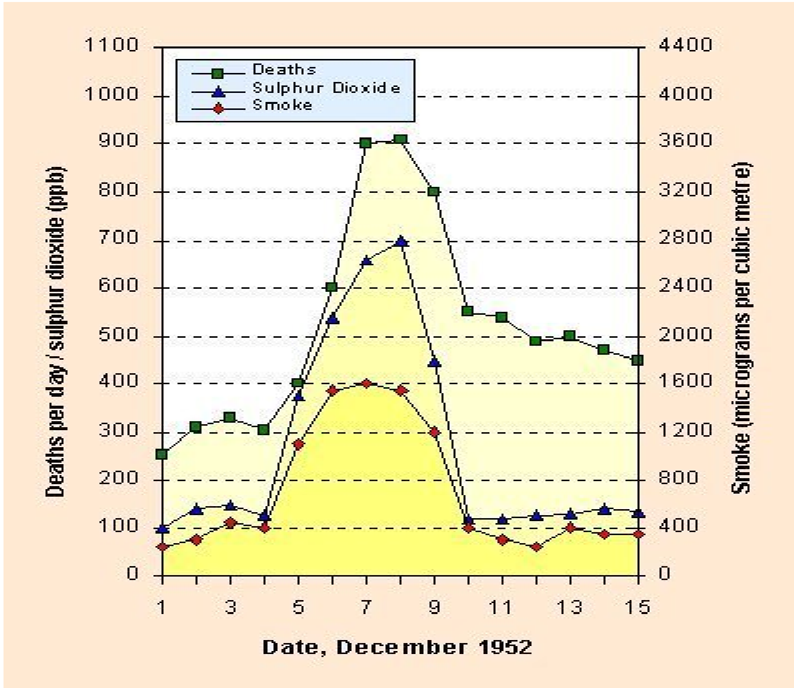
More detailed research on exposure to indoor smoke and its impact on respiratory diseases in developing countries began in the 1960s and 1970s in India, Nigeria, and Papua New Guinea (Ezzati and Kammen, 2002). Due to an increasing number of research projects since the 1980s, the issues of household energy use, health impacts of IAP, and related policy interventions have recently appeared on the agenda of research and policy communities.

IAP related research falls into three categories: emissions and exposure assessment, health impact assessment, and intervention strategies or programs. In addition, there are several review articles that summarize current knowledge and recommend research directions, including Smith et al (2000), Ezzati and Kammen (2002), Zhang and Smith (2007), and Duflo et al (2008).

A. Emissions and Exposure Assessment

For emissions and exposure assessment, research has focused on finding temporal and spatial characteristics of emissions and individual exposure patterns. Personal or area monitors to record particulate matter (PM) or carbon monoxide (CO) concentrations are

Figure 1-1. London Smog Disaster of 1952



Source: http://www.portfolio.mvm.ed.ac.uk/studentwebs/session4/27/greatsmog52.htm

often used in these studies. The research finds that emissions from biomass stoves vary greatly over short time intervals and these fluctuations relate to combustion characteristics (such as energy density, combustion temperature, and air flow) and cooking behavior. For example, the emission peaks occur when fuel is added or removed, the stove is lit, the cooking pot is placed on or removed from the fire, or food is stirred. In addition, pollution concentrations are found to exhibit a pronounced spatial gradient rather than instantaneous mixing (Ezzati and Kammen, 2002). For example, Saksena et al (1992) reported total suspended particulate (TSP) concentrations of 20 milligrams per cubic meter (mg/m^3) or more near the cooking location in India, and Ezzati and Kammen (2001) recorded peak PM concentrations greater than 50 mg/m^3 in the immediate vicinity of the cooking fire in Kenya. Much lower PM concentrations were reported in the rest of the kitchen and other rooms in the household.

The complexity of emission characteristics further complicates the assessment of individual exposure patterns. The complete time-activity budgets of individuals are also important determinants of exposure. In order to reduce cost and simplify evaluation of health impacts or intervention programs, a widely-adopted set of indicators for exposure to indoor smoke are yet to be developed from research on emissions and exposure assessment.

B. Health Impact Assessment

For health impact assessment, there have been a growing number of research studies showing a strong correlation between IAP and negative health outcomes. A number of studies have found associations between IAP and acute lower respiratory infections (ALRI) (Smith et al, 2000, Ezzati and Kammen, 2001a, 2001b, Dherani et al, 2008), chronic obstructive pulmonary diseases (Bruce et al, 2000, WHO, 2002), and lung cancer (Mumford, 1987, Smith, 1993). In addition, there is emerging evidence that IAP increases the risk of other child and adult health problems, including low birth-weight, perinatal mortality, asthma, middle ear infection, tuberculosis, nasopharyngeal cancer, cataracts, blindness, and cardiovascular disease (WHO 2002). More recently, Zhang and Smith (2007) undertook a detailed meta-analysis of 200 publications regarding IAP in China and showed that most of the studies find a strong correlation between IAP and observed health effects including respiratory illness, lung cancer, chronic obstructive pulmonary disease, weakening of the immune system, and reduction in lung function.

However, due to the cost of measurement, most studies use indirect measures of exposure as proxies. For example, Smith et al (2000) reviewed thirteen recently published studies (summarized in Table 1-1) that quantitatively address the relationship between exposure to household biomass smoke and ALRI in young children in developing countries. All studies used indirect measures of exposure, such as fuel type, housing characteristics, or aggregate measures of time spent near fires. Many of these studies use the case-control approach by dividing the study group into those who are affected by disease and those who are not at one point in time. For example, households using an open wood fire are compared to those who cook with cleaner fuels such as kerosene or LPG. However, as discussed above, indirect exposure proxies mask the complexities of exposure to indoor smoke and may result in biased estimates. Furthermore, such studies are not able to quantify the relationships between exposure level and risk, providing little information for estimating the potential health gains that might result from reducing exposure by different amounts.

In addition to using indirect exposure proxies, many studies fail to deal adequately with confounding issues (Bruce et al, 2000). Households who have taken measures to improve their indoor air quality may do so following improvements in their socioeconomic characteristics (e.g. income, education, nutrition and medical care), which strongly influence many health outcomes (Bruce et al, 1998). Thus, inadequate control for these confounding factors is likely to result in an overestimate of the health impacts of IAP. More recent studies have given more attention to confounding issues. For example, some have adjusted for factors such as socioeconomic status, parental education,

Table 1-1. Studies that Quantify Biomass Fuel Use and ALRI in Children under 5 in Developing Countries

Study	*Design*	*Case definition*	*Exposure*	*Confounding adjusted*	*Comments*	*OR (95% CI)*
Rural South Africa (1980) Natal (Kossove)[58]	Case control, 0–12 months, 132 cases, 18 controls	Outpatient cases: Wheezing, bronchiolitis & ALRI; Clinical + *x* ray. Controls: Non-respiratory problems	Asked: "Does the child stay in the smoke?" Prevalence = 33%	Routine data collection: ● number of siblings ● economic status Examined, not adjusted	Only 63% of 123 *x* rayed had pneumonic changes. Control group was small. Exposure assessment was vague.	4.8 (1.7 to 13.6)
Rural Nepal (1984–85) Kathmandu Valley (Pandey *et al*)[53]	Cohort, 0–23 months, 780 (study 1), 455 (study 2)	Two-weekly home visits: ARI grades I–IV (Goroka) Breathlessness	Asked mothers for average hours per day the child near fireplace. In study 1, same team asked about exposure and ARI > possible bias 77% exposed over 1 hour	Since homes were "homogeneous" confounding not taken into account	Dose response relationship found Exposure assessment not validated	2.2 (1.6 to 3.0)
Rural Gambia (1987–88) Basse (Campbell *et al*)[54]	Cohort, 0–11 months, 280	Weekly surveillance. Mother's history of "difficulty with breathing" over subsequent 3 month period	Reported carriage of child on the mother's back Prevalence = 37%	Adjusted for ● birth interval ● parental ETS ● crowding ● socioeconomic score ● nutritional indicators ● vaccination status ● no. of health centre visits ● ethnic group ● maternal education ● other	Father's ETS only other significant factor. Cautious about interpretation, ability to deal with confounding, and to establish causation where exposure and incidence high	2.8 (1.3 to 6.1)
Urban, Argentina (1984–87) Buenos Aires (Cerqueiro *et al*)[67]	Case-control, 0–59 months Cases: 516 inpatients; 153 outpatients, Controls: 669	Three hospitals: Cases: ALRI within previous 12 days Controls: well baby clinic or vaccination, matched by age, sex, nutritional status, socioeconomic level, date of visit, and residence.	Interview with mother: Household heating by charcoal; heating with any fuel; bottled gas for cooking	None, but success of matching verified. Multivariate analysis "currently underway"	No data available re charcoal heating in outpatient households. Chimney smoke nearby found to be associated (OR 2.5–2.7) with ARLI in both kinds of patients. ETS not significant for either	9.9 (1.8 to 31.4) for charcoal heat for inpatients 1.6 (1.3 to 2.0) for any heating fuel in inpatients 2.2 (1.2 to 3.9) for gas cooking in outpatients
Rural Zimbabwe (?) Marondera (Collings *et al*)[57]	Case control, 0–35 months, 244 cases, 500 controls	Hospital: Cases: Hosp ALRI, clinical and *x* ray. Controls: Local well baby clinic	(a) Questionnaire on cooking/exposure to woodsmoke (b) COHb (all) (c) TSP (2 h during cooking): 20 ALRI and 20 AURI cases 73% exposed to open fire	Questionnaire: ● maternal ETS ● overcrowding ● housing conditions ● school age sibs ● paternal occupation not adjusted	Confounding: only difference was number of school age sibs, but not adjusted. COHb not different between ALRI and AURI. TSP means: ALRI (n=18) 1915 μg/m³ AURI (n=15) 546 μg/m³	2.2 (1.4 to 3.3)
Rural Gambia (?) Upper River Division (Armstrong and Campbell)[56]	Cohort, 0–59 months, 500 (approx.)	Weekly home visits: ALRI clinical and *x* ray	Questionnaire: Carriage on mother's back while cooking	Questionnaire: ● parental ETS ● crowding ● socioeconomic index ● number of siblings ● sharing bedroom ● vitamin A intake ● no. of wives ● no. of clinic visits Adjusted in MLR	Boy/girl difference could be due to greater exposure. Report carriage on back quite a distinct behaviour so should define the two groups fairly clearly with low level of misclassification	Approach (1) (all episodes) M: 0.5 (0.2 to 1.2) F: 1.9 (1.0 to 3.9) Approach (2) (1st episode) M: 0.5 (0.2 to 1.3) F: 6.0 (1.1 to 34.2)
Urban Nigeria (1985–86) Ibadan (Johnson and Aderele)[62]	Case control, n=103+103, 0–59 months	Cases: Hospitalised for ALRI (croup, bronchiolitis, pneumonia, empyema thoracis) based on clinical, *x* ray, and biolab workup. Controls: infant welfare clinic, age and sex matched, no respiratory disease	Interview Type of cooking fuel used at home (wood, kerosene, gas)	None	Age, nutritional status, ETS, crowding, and location of cooking area also not significant.	NS

Urban Nigeria (1985–86) Ibadan (Johnson and Aderele)[62]	Case fatality, n=103, 0–59 months	Cases: Death in hospital among ALRI patients (see above)	Interview Type of cooking fuel used at home (79 = kerosene, gas = 5, wood = 16, other = 3)	None	Overall case fatality rate = 7.8%. 5 of 8 deaths were from wood burning homes; one additional death had partial exposure to wood smoke. Poor nutrition (1.8×), low income (1.5×), low maternal literacy (2.1×) were more frequent in wood burning homes. ETS rates were similar. Yet paternal income, maternal education, household crowding, ETS not related to case fatality rate	12.2 ($p<0.0005$) for those exposed to wood smoke compared with those exposed to kerosene and gas
Rural Tanzania (1986–87) Bagamoyo District (Mtango *et al*)[60]	Case-control Cases: ALRI deaths = 154 Other deaths = 456 Controls = 1160 0–59 months	Cases: Verbal autopsy certified by physician of all deaths in period. Controls: Multistage sampling (40 of 76 villages). Children with ALRI were excluded	Household interview; ● Child sleeps in room where cooking is done ● Cook with wood	Village, age, questionnaire respondent, maternal education, parity, water source, child eating habit, whether mother alone decides treatment.	About 95% of all groups cook with wood. No tendency to be different distances from road. Perhaps confusion of ALRI with other diseases (e.g. measles). Water not from tap had OR = 11.9 (5.5 to 25.7). Models with all deaths, pneumonia deaths, and non-pneumonia deaths all had same significant risk factors. No difference in source of treatment by location where child sleeps. Maternal education, religion, crowding, and ETS, not significant	All deaths: 2.8 (1.8 to 4.3) for sleeping in room with cooking. 4.3 for pneumonia only. 2.4 for other deaths
Rural Gambia Upper River Division (de Francisco *et al*)[61]	Case-control Cases: 129 ALRI deaths Controls: 144 other deaths 270 live controls 0–23 months	Cases: Verbal autopsy confirmed by 2 of 3 physicians. Controls: Matched by age, sex, ethnic group, season of death, and geographic area	Indoor air pollution index based on location and type of stove, carrying of child while cooking, and parental ETS (details not provided)	Cases vs. live controls: Adjusted for significant factors in univariate analysis: socioeconomic score, crowding, parental ETS, and nutrition indicators plus maternal education. No significant factors for cases vs. dead controls.	Only other significant risk factor remaining after multiple conditional logistic regression was whether child ever visited welfare clinic OR = 0.14 (0.06 to 0.36) Misclassification of ALRI deaths (e.g. confusion with malaria) is possible reason for lack of significant difference between cases and dead controls.	5.2 (1.7 to 15.9) for cases vs. live controls
Urban Brazil (1990) Porto Alegre (Victora *et al*)[64]	Case control, 0–23 months, 510 cases, 510 controls	Cases: ALRI admitted to hospital, clinical and X-ray. Controls: Age matched, neighborhood	Trained field worker interview: ● Any source of indoor smoke (open fires, woodstoves, fireplaces) ● Usually in kitchen while cooking	Interview: ● cigarettes smoked ● housing quality ● other children in hh ● income/education ● day centre attendance ● history of respiratory illness ● (other) Hierarchical model/MLR	Only 6% of children exposed to indoor smoke. Urban population with relatively good access to health care. Not representative of other settings in developing countries	Indoor smoke: 1.1 (0.61 to 1.98) Usually in the kitchen: 0.97 (0.75 to 1.26)
Urban and rural India (1991) South Kerala-Trivandrum (Shah *et al*)[63]	Case control, 2–60 months, 400 total	Hospital: Cases: Admitted for severe/very severe ARI (WHO definition). Controls: Outpatients with non-severe ARI	History taken, including ● type of stove, with "smokeless" category ● outdoor pollution	History: ● smokers in house ● number of siblings ● house characteristics ● socioeconomic conditions ● education ● birth weight etc. Adjusted in MLR	This is a study of the risk factors for increased severity, as the controls have ARI (non-severe). On MLR, only age, sharing a bedroom, and immunisation were significant. Exposure assessment was vague and invalidated	"Smokeless" stove: 0.82 (0.46 to 1.43).
Rural Gambia (1989–1991) Upper River Division (O'Dempsey *et al*)[55]	Prospective case-control, n=80+159, 0–59 months	Attending clinic. Cases: if high respiratory rate, transported to Medical Research Council where physician diagnosed pneumonia after lab tests and *x* ray. Controls: selected randomly from neighbourhood of cases, matched by age	Household questionnaire: Mother carries child while cooking	Adjusted for mother's income, ETS, child's weight slope, recent illness, and significant illness in last six months.	No effect of bednets, crowding, wealth, parental education, paternal occupation, age of weaning, and nutritional status. ETS OR = 3.0 (1.1 to 8.1). Aetiological (preventive) fraction for eliminating maternal carriage while cooking = 39%; for eliminating ETS in house = 31%. May be reverse causality, i.e. sick children being more likely to be carried.	2.5 (1.0 to 6.6)

Source: Smith et al (2000)

breastfeeding, nutritional status, environmental tobacco smoke, crowding, and vaccination status. However, the adequacy of control of and/or adjustment for confounding factors has varied considerably (Dherani et al, 2008).

To avoid selection bias and confounding effects, experimental studies that allow randomization of the study group, especially randomized intervention studies, have been proposed. Randomized Exposure Study of Pollution Indoors and Respiratory Effects in Guatemala started in October 2002 was the first randomized controlled trial ever performed on health effects from solid fuel use (Diaz et al, 2007). Its goal was to assess the effect of improved stoves on exposure and health outcomes in a rural population reliant on wood fuel. The study randomly selected women who either had a child less than four months old or were pregnant at the time the study began. Each household was followed until the infants reached 18 months of age. Health assessments were conducted every six months covering respiratory symptoms, eye irritation, headaches, and backaches. The study confirmed that use of the improved stove significantly reduces exposure to IAP and found that women in the treatment group had reductions of sore eyes, headaches, and sore throats compared to the control group. Children in the treatment group experienced reductions in crying and sore eyes (Diaz et al, 2007).

However, the design of randomized treatments is not immune to problems. First, whether households respond to incentives to use an improved stove and how they use it may be a function of unobserved factors, which may result in biased estimates. Second, the field experiment approach cannot readily address the issue of chronic risk because chronic risk is dependent on accumulated exposure. Long observation periods are required to show effects of any intervention on chronic risk. Further, those accustomed to long term exposure may be more reluctant to adopt alternatives. Third, experimental studies are highly dependent on individual behavior and do not capture the complex determinants and patterns of exposure. So the findings are hard to apply to large-scale intervention efforts (Ezzati and Kammen, 2002).

C. Intervention Strategies

For intervention strategies or programs, most current research has focused on improved stoves and fuels, which provide more affordable options than a complete shift to nonsolid fuels. A number of studies examine whether improved stoves reduce IAP. For example, McCracken and Smith (1998), Albalak et al (2001), Ezzati and Kammen (2002b), and Diaz et al (2007) have all found that various types of improved cooking stoves have resulted in reductions of toxic pollutants. However, even though improved cooking stoves reduce IAP, the effects could be mitigated by behavioral responses. For example, if there is less smoke near the stove, individuals may choose to spend more time around the stove than they previously did. Thus, there is still little understanding of the impact of stoves on health and whether or not promoting improved stoves is a cost-effective strategy.

A few studies, such as Heltberg, R. (2004, 2005), Ouedraogo (2005), and Jack (2006) have examined factors determining household fuel choices. Heltberg found that in addition to income, factors such as opportunity costs of time used to collect firewood, education level, and access to electricity also play an essential role. However, there is little systematic evidence indicating which factors determine household behavior with respect to fuel use and motivate households to switch cooking technologies. In addition, the benefits of adopting modern cooking technologies that can reduce IAP exposure have not been quantified and no welfare analysis has been done to evaluate and compare welfare changes from different policy interventions. Finally, long-term performance of improved stoves or modern fuel promotion programs has not been monitored, and wider environmental and socio-economic implications are not well understood (Ezzati & Kammen, 2002).

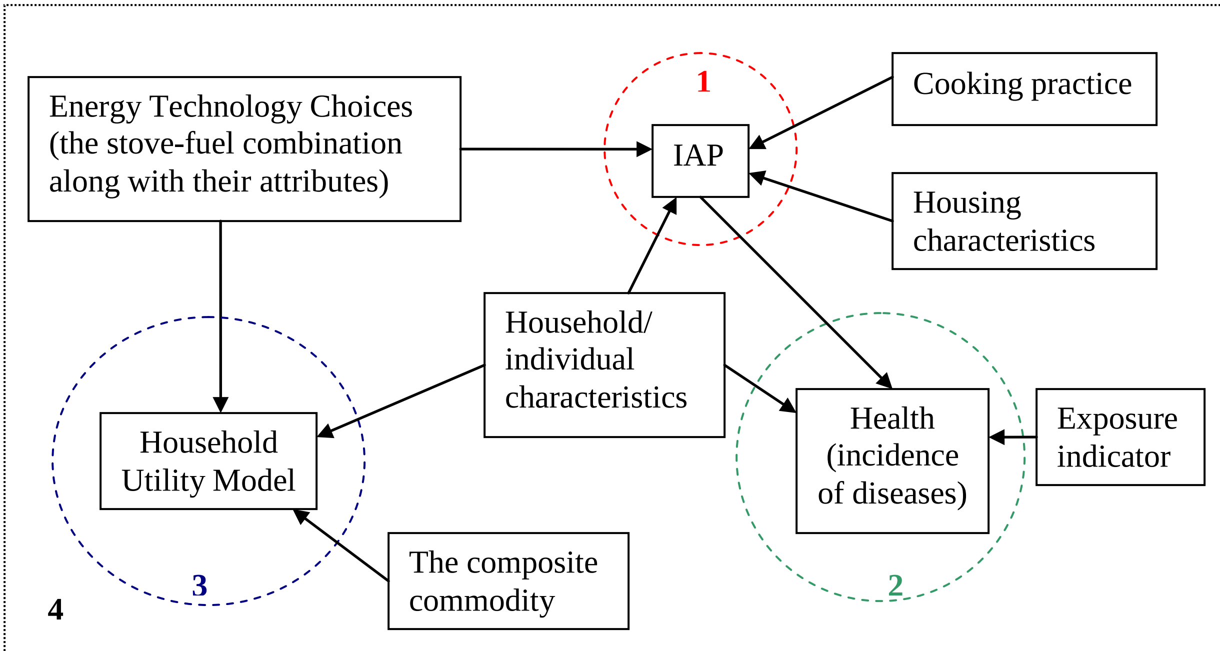
Aside from a recent PhD dissertation by Darby Jack (2006), no study has explicitly determined why people use household energy technologies that can make them sick or even cause death. In his dissertation, using a panel household survey dataset from Peru, Jack explored three issues related to this puzzle: (1) factors affecting household fuel choices, (2) evidence of social learning in fuel choice patterns, and (3) health impacts of indoor air pollution. Although he provides additional insights on household behavior regarding energy use, such as a social learning effect, his study suffers data limitations similar to many other studies. To assess the health impacts of IAP, Jack used fuel choice to proxy for exposure to IAP due to unavailability of direct IAP concentrations. As discussed earlier, use of this proxy masks the complexities of exposure to indoor smoke and may result in biased estimates. In addition, the health outcomes used in his study were self-reported. Thus, there may be systematic errors in the health variables depending on whether people perceive themselves as ill. This is likely to vary systematically according to education, access to information, occupation, and other factors.

Methodology Overview

To study the research questions raised in this chapter, I develop an analytical framework that can be illustrated as in Figure 1-2. The framework can be divided into four modules corresponding to the four sets of questions.

Module 1 studies the determinants of IAP. Controlling for household characteristics, the factors considered include energy technology choices, housing characteristics, and cooking practices. This is done using IAP concentrations that are monitored over a 24-hour period. I compare how these factors determine different measures (such as mean and 95th percentile) of the IAP concentrations.

Figure 1-2. Analytical Framework



Module 2 analyzes the health impact from exposure to IAP, which is determined by IAP concentrations and individual exposure indicators. This is done controlling for household and individual characteristics. For exposure assessment, instead of using stoves and fuels as exposure proxies, I use IAP concentrations in the kitchen and individual's typical kitchen presence as an indicator to examine exposure to IAP. For health outcomes, in addition to using self-reported respiratory symptoms, I also use objectively measured lung capacity to avoid possible self-reporting bias. Furthermore, I use household fixed effects and instrumental variables to cope with confounding problems.

Module 3 represents household behavior with respect to energy technology choices through utility maximization. In this component of the model, household utility is determined by a composite commodity and energy technology choices conditional on household characteristics.

I assume households make energy technology choices based on technology attributes such as cost, cleanliness, and convenience. How households value these attributes varies with households characteristics.

Module 4 evaluates welfare effects of different policy interventions based on the estimated household utility function from Module 3. The policy scenarios focus on interventions that can change energy technology attributes, such as replacing traditional stoves with improved stoves, improving kitchen ventilation, and phasing out LPG subsidies.

Main Contribution

Despite the importance of health risks caused by IAP and increased interest among research and policy communities, because of limited data and problem complexity, no study has been able to develop a coherent framework that can link household behavior with actual IAP level and the health impact sufficient to conduct welfare analysis. The main contribution of this dissertation is a unified framework to link the relationships among household energy use, IAP level, and health consequences and to quantify the welfare changes from alternative policy interventions.

With the tight government budgetary constraints that usually exist, it is important to prioritize public sector investments on the basis of expected benefits. The framework developed here is able to quantify the welfare changes from alternative policy interventions. For example, if a program aims to promote improved stoves, this framework can estimate how much households will value an improved stove and whether a subsidy on the stove is necessary. The results can reveal how much they are willing to pay for it if they are convinced of the improved features. The model can also evaluate how much households can benefit from improved kitchen ventilation. As switching to clean fuels is the most effective way to reduce indoor air pollution, the model can examine the factors that determine households' fuel switching and whether subsidizing an LPG stove can make a difference. Since LPG price is currently highly subsidized and the Indian government is considering phasing out the subsidies, the model can evaluate the impact of this policy on household energy technology choices and estimate welfare change from phasing out LPG subsidies.

Dissertation Structure

The remainder of this dissertation is organized as follows. Chapter 2 discusses the sources of data used in this dissertation and their structure. Chapter 3 describes the methodology and results for Module 1 and identifies the determinants of IAP. Controlling for household characteristics, the factors considered include energy technology choices, housing characteristics, and cooking practices. Multiple-stove use and quantities of fuel use are modeled to capture detailed energy technology choice patterns. Chapter 4 presents the methodology and results for Module 2 to evaluate the health impacts from exposure to IAP. Chapter 5 presents the methodology and results of Module 3, examining household behavior with respect to energy technology choices through utility maximization. Using the estimates from Modules 1 and 2, Module 3 is able to estimate household utility functions and examine the factors that can affect household energy technology choices. Chapter 6 presents welfare analysis of policy simulations based on the model estimated in Chapter 5 and discusses policy implications. Chapter 7 presents conclusions of the analysis.

Chapter 2. Data Overview

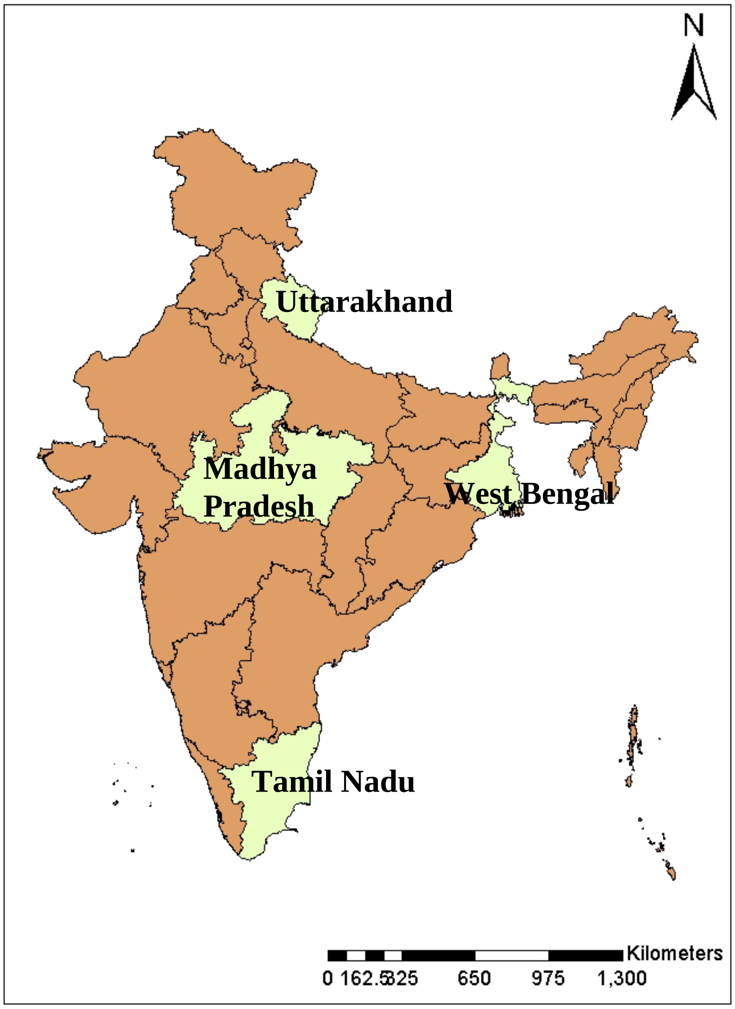
Data Sources

This dissertation relies primarily on two surveys recently conducted in India: a multi-topic representative sample survey called the India Human Development Survey 2005 (IHDS) and a social science and environmental health survey entitled Health, Environment, and Economic Development (HEED). The IHDS was conducted jointly by the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi, and funded by the National Institutes of Health. It is a nationally representative, multiple topic survey of 41,554 households in 1503 villages and 971 urban neighborhoods across India. Two one-hour interviews in each household covered health, education, employment, economic status, marriage, fertility, gender relations, and social capital. In addition to the household-level survey, IHDS includes a village survey that compiles information on the village economic and social infrastructure and the labor market.

The HEED survey was an extension of the IHDS survey. It was jointly organized by researchers at the University of Maryland, the NCAER, the University of California (UC), Berkeley, the World Bank, the Energy Research Institute (TERI), and Sri Ramachandra Medical College (SRMC). It involves 622 households with about 3000 individuals in four states: Uttarakhand[1] (UA), West Bengal (WB), Madhya Pradesh (MP), and Tamil Nadu (TN). The study locations are shown in Figure 2-1. The 622 households are a sub-sample of the IHDS organized by the University of Maryland and the NCAER. In addition to the standard IHDS survey questionnaires, a fuel and cooking supplemental questionnaire designed by researchers from the World Bank, the University of Maryland, and the NCAER was added to this sub-

[1] At the time of the survey, the state used the interim name, Uttaranchal, whereas in January 2007 the state name was officially changed to Uttarakhand.

Figure 2-1. HEED Study Locations



sample to get more detailed information on households cooking fuel usage. The 24-hour IAP monitoring data, the IAP post-monitoring data, and health information including self-reported symptoms and doctor-measured lung function data were jointly collected by TERI and SRMC. TERI was responsible for data collection in Uttarakhand, West Bengal, and Madhya Pradesh. SRMC was responsible for data collection in Tamil Nadu. UC Berkeley developed the IAP monitoring protocols, held on-site IAP monitoring training, and processed the 24-hour IAP monitoring data.

Both the IHDS and HEED surveys were fielded between late 2004 and early 2005. Together, the two surveys provide uniquely rich information on household energy use, the household environment, health, and development in India.

Data Structure

The HEED survey includes 622 households from four geographically and culturally diverse states in India. Within each state, two districts were randomly selected. Within each district, three villages (two rural, one urban) were randomly selected. Each village includes up to several hundred households. To select the study households, the field team first conducted a rapid assessment of all households in the village. The team members went to each household and asked several questions such as primary fuel type and kitchen type. After the completion of the rapid assessment, a stratified random sample of 25 households based on fuel and kitchen type was drawn (Naumoff, 2007). Approximately 150 households were sampled per state.

The HEED data includes several parts. The part administrated through the NCAER includes multiple topics. The data that are directly related to this study record household energy characteristics, cooking practices, ventilation conditions, housing characteristics, health, consumption, education, and other household socioeconomic indicators. The health questions include short-term mortality and major morbidity. The ones related to respiratory symptoms include coughing and shortness of breath. In addition, the NCAER questionnaire includes health belief questions such as "Is smoke from a wood/dung burning traditional stove good for health, harmful for health or do you think it doesn't really matter."

TERI and SRMC collected 24-hour IAP monitoring data, post-monitoring data, and health data. IAP monitoring data includes 24-hour measurements[2] of concentrations of fine particles less than 2.5 microns (μm), denoted as PM 2.5, and CO concentrations in all study households. PM 2.5 was measured using the UCB Particle Monitor, which was placed in the kitchen area according to the following standard protocol: (1) approximately 100 cm from the edge of the combustion zone, (2) at a height of 145 cm above the floor, (3) at least 150 cm away (horizontally) from doors and windows, where possible (Naumoff, 2007).

After the IAP monitoring data was collected, a post-monitoring questionnaire was used to survey each household to assess household energy characteristics such as fuel type, kitchen type, stove type, and cooking time during the monitoring period. The questionnaire was designed collaboratively by the TERI, SRMC, and UC Berkeley research teams. Many questions are compatible with the NCAER's fuel and cooking supplemental questionnaire. However, one important distinction is that the post-monitoring questions were asked for the situation for the 24-hour monitoring period while the NCAER's fuel and cooking supplemental questions were asked for the typical situation in the past year or past month.

The health questionnaire was designed to assess each participant's respiratory symptoms, including coughing, shortness of breath, phlegm, and wheeze. For the questionnaire design, TERI and SRMC took two different approaches. The questionnaire administered by TERI in Madhya Pradesh, Uttarakhand, and West Bengal were based on the British Medical Research Council Questionnaire. The questionnaire administered by SRMC in Tamil Nadu was designed to mimic a physical examination (Naumoff, 2007). In addition to respiratory symptoms, the questionnaire includes assessment of allergies, back pain, and burns and scalds. In Chapter 4,

[2] The actual measurements ranged from 22 to 26 hours.

which focuses on the analysis of health impacts of indoor air pollution, I test whether the data from the two questionnaires is compatible.

At the same time the health questionnaire was administered, lung function measurements were recorded for each participant older than 15 years. The measurements included forced vital capacity (FVC), forced expiratory volume in 1 second (FEV1), and the ratio between the two (FEV1/FVC). Spirometry was conducted in a standing position and all spirometry measurements were recorded in adherence to the joint American Thoracic Society (ATS) and European Respiratory Society guidelines (Naumoff, 2007, Miller, Hankinson et al, 2005). The analysis uses the best of three readings. Height was also measured by the survey team according to standard protocol.

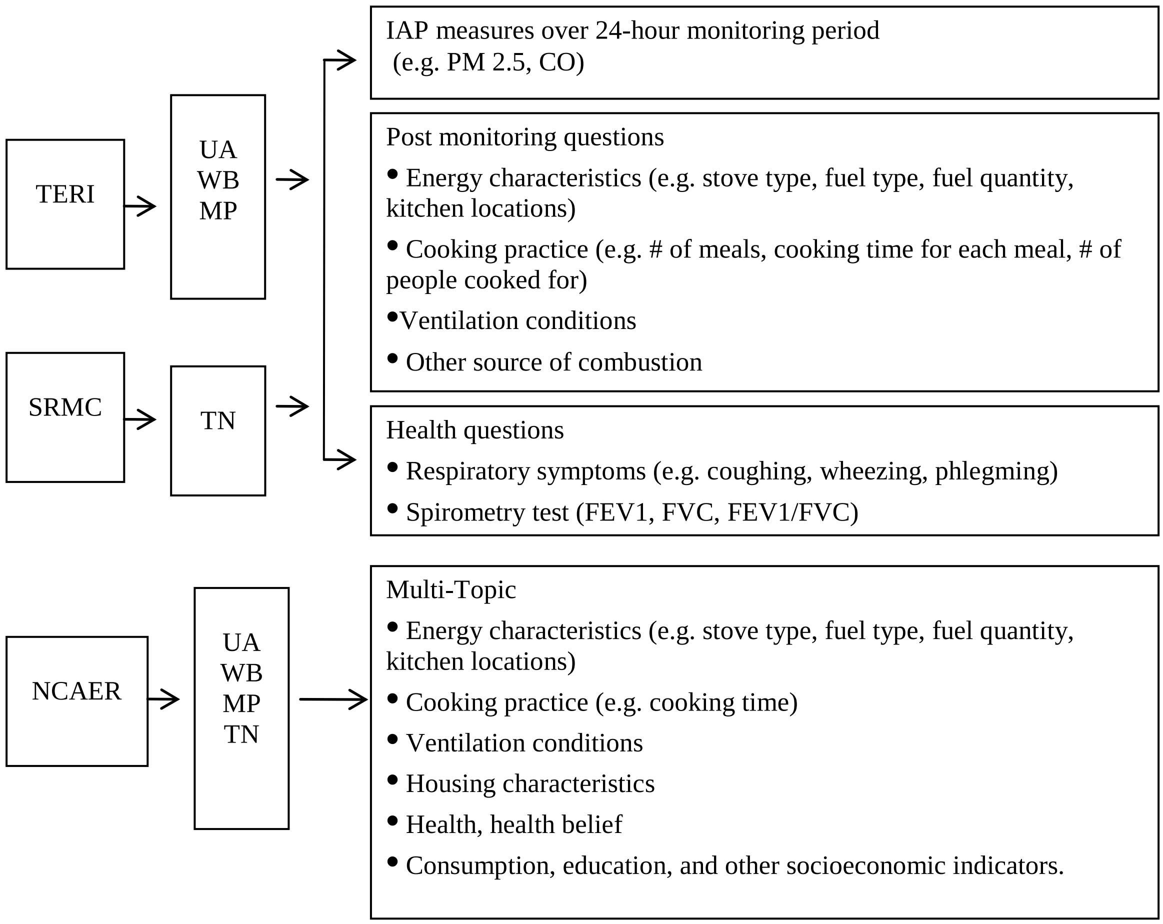
The HEED data structure can be illustrated as in Figure 2-2.

Overview of Household Energy Use in India

Traditional biomass fuels are still commonly used for cooking and heating in India. Table 2-1 shows primary stove use and energy use in India by urban and rural households using both IHDS and HEED data. Since IHDS is a national representative sample, I refer to IHDS data for the following discussion. As Table 2-1 shows, 27% of Indian households use clean stoves such as LPG, kerosene, and electric stoves as their primary stoves, while 90% of rural households and 40% of urban households still rely on biomass as their primary cooking fuel.

To mitigate the negative effects of traditional biomass stoves, the National Program for Improved Chulhas (NPIC) was initiated in 1983 to promote installation of improved stoves that improve fuel efficiency and reduce IAP generated by burning traditional fuels. However, many of the intended benefits of the program were not realized due to poor maintenance, stove

Figure 2-2. HEED Data Structure



modifications by users, and deterioration of the stoves themselves. The low cost and sometimes poor designs and materials used for the program resulted in stoves lying broken and unused. As a result, the Government decided to terminate this national stove program in 2002, and decentralize the full implementation authority and funding support to the state level. Unfortunately, the consequence of this handover has not been positive. Some states continued in a fragmented manner and others closed down the program completely (Barnes et al, forthcoming). As the IHDS data shows, improved stoves are used by only 5% of rural households and 6% of urban households currently.

The IHDS reports energy use not only for cooking, but also for lighting, heating, and other purposes. In fact, electricity use is the primary energy source for lighting while very few households use electricity for cooking in India. When electricity is not available, kerosene is most commonly used for lighting. Thus, electricity and kerosene have relatively high market penetration rates compared to other fuels. As a major clean cooking fuel, LPG use is quite limited, especially in rural areas. Only 22% of rural households use LPG compared to 71% of urban households. However, only 5% of households used LPG 10 years ago. Thus, penetration of LPG has increased remarkably, especially in urban areas.

Households in India often use multiple types of cooking fuels and cooking stoves, and the pattern tends to vary with the socio-economic profile of households. As shown in Table 2-2, 38% of rural households use both traditional biomass and clean cooking fuels (mainly kerosene and LGP) while only 6% of rural households have switched completely to clean cooking fuels. In contrast, 65% of urban households use only clean cooking fuels while 24% of urban households also use traditional biomass in addition to clean fuels. As expected, the wealthier households are more likely to switch to clean cooking fuels because cooking fuels are more expensive.

Because HEED has more detailed information including not only fuel characteristics and household characteristics but also indoor air pollution and health information, I use HEED as the basic data set for the following modules. Although HEED is not a nationally representative sample, Table 2-1 and Table 2-2 show that the energy use patterns in HEED are generally comparable to IHDS. Thus, the results drawn from the HEED data appear to have wide applications in India.

Table 2-1. Types of Energy Use by Urban and Rural Households in IHDS and HEED

Household Choice	IHDS			HEED		
	Total	Rural	Urban	Total	Rural	Urban
Sample size (Number of HH)	40731	64%	36%	622	66%	34%
Primary Stove						
Open fire	23%	28%	13%	20%	23%	15%
Traditional stove	45%	57%	21%	50%	56%	37%
Improved stove	5%	5%	6%	1%	2%	0%
Gas/kerosene/electricity	27%	10%	60%	29%	19%	48%
Energy Use						
Firewood	71%	91%	36%	80%	88%	64%
Wood chips	N/A	N/A	N/A	18%	20%	14%
Crop Residue	14%	20%	2%	17%	23%	7%
Dung Cakes	37%	50%	13%	43%	49%	31%
Charcoal				1%	1%	2%
Coal	5%	3%	7%	8%	6%	14%
Kerosene	76%	87%	54%	78%	81%	73%
LPG	40%	22%	71%	35%	32%	41%
Electricity	78%	69%	95%	78%	75%	84%

Source: IHDS survey and HEED survey

Table 2-2. Types of Cooking Fuel Use by Indian Households

Household Characteristics	IHDS			HEED		
	Clean Only	Biomass & Clean	Biomass Only	Clean Only	Biomass & Clean	Biomass Only
By Urban and Rural						
Rural	6%	38%	55%	9%	32%	60%
Urban	65%	24%	11%	42%	29%	29%
By Asset Quintile						
1st	2%	29%	70%	5%	12%	83%
2nd	6%	34%	61%	14%	26%	60%
3rd	15%	40%	45%	15%	34%	52%
4th	36%	41%	23%	26%	40%	34%
5th	64%	30%	6%	45%	42%	12%

Source: IHDS survey and HEED survey

Conclusions

In summary, this dissertation relies primarily on two recent surveys in India—IHDS and HEED. The IHDS is national representative survey covering multiple topics whereas the HEED survey samples four states and focuses on health and fuel use. Together, the two surveys provide uniquely rich information that allows exploration of the issues raised in Chapter 1. Because

HEED has more detailed information including not only fuel characteristics and household characteristics but also indoor air pollution and health information, HEED is used as the basic data set for the following modules. Since the HEED sample is a sub-sample of IHDS, the IHDS is used whenever necessary to complement the HEED data. As the energy use patterns in HEED are generally comparable to IHDS, the results drawn from the HEED data can have wide applications in India.

Chapter 3. Determinants of Indoor Air Pollution

Introduction

Although there are hundreds of chemicals in biomass smoke including well-known health-damaging pollutants such as carbon monoxide, hydrocarbons, and nitrogen oxides, fine particles less than 10 microns (μm) (PM 10) and especially less than 2.5 μm (PM 2.5) in diameter are considered the most harmful to health because they are small enough to be inhaled and transported deep into the lungs (Kleeman, 1999 and WHO, 2002). For biomass smoke, the modal size of particles is between 0.2 and 0.4 μm, and 80% to 95% of particles are smaller than 2.5 μm (Hueglin et al. 1997). In this study, the concentration of PM 2.5 in mg/m^3 is used as the indicator of indoor air pollution. Although there is no safe level of particulate air pollution, the lower the better. For comparison, the US national ambient air quality standard for the annual mean of PM 2.5 concentration is 0.015 mg/m^3 (EPA, 2006). In the HEED sample, a concentration of 0.35 mg/m^3 or greater is very common. Table 3-1 shows the basic statistics of PM 2.5 concentrations at the mean, median, and the 95th percentile in kitchens and living areas based on a 24-hour continuous monitoring period, respectively. The average PM 2.5 concentrations in all these measures have been far beyond the US national ambient air quality standard. In particular, some of the 95th percentile PM 2.5 concentrations in kitchens are extremely high.

To investigate the determinants of IAP exposure, I use regression analysis to explore the relationships between the PM 2.5 concentrations in kitchens and a set of variables that describe the household energy technology, cooking practices, and housing characteristics in addition to control variables for temperature, humidity, and state of residence. Identifying the role of household energy technology is my primary interest and can be viewed as a combination of cooking fuel and stove type. In terms of types of cooking fuels, firewood, crop residues, and dung cake are commonly used forms of traditional biomass, whereas kerosene and LPG are commonly used clean fuels. In addition, about 30 households report the use of coal in West Bengal and Madhya Pradesh. Five households report the use of charcoal and a couple of households also report the use of biogas. Basic statistics for the explanatory variables used in this chapter are also provided in Table 3-1.

In terms of types of cooking stoves, the following types of stoves have been reported: open fire (e.g., three stone stoves), traditional stoves, improved stoves (those that burn traditional fuels but are more efficient and cleaner than traditional stoves), and clean stoves (those that burn clean fuels such as kerosene, LPG, or biogas). About 50% of Indian households use only one cooking stove and the other half use one primary stove and one secondary stove. Very few households (0.65% in the HEED sample) use more than two cooking stoves.

Due to the complication of multiple types of cooking fuel and cooking stoves and their interactions, there are a number of ways to model household energy technology. Considering the sample size limitation, I characterize the choice in two ways: first, by the choice of stove type and, second, by the fuel type choice.

Energy Technology Choices

Because an open fire can be treated as a simplified traditional stove, cooking stoves can be categorized into three types: (1) traditional, (2) improved, and (3) clean. Both traditional stoves and improved stoves use traditional biomass such as firewood, crop residues, and dung cakes. Occasionally (5% in the HEED sample), charcoal and coal are used. Although charcoal and coal are generally cleaner than traditional biomass, they are grouped with the traditional biomass and classified as dirty fuel in this model because they are much dirtier than clean fuels.

Table 3-1. Basic Statistics of PM 2.5 Concentrations (mg/m^3) and Explanatory Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
PM 2.5 Concentrations				
Mean PM 2.5 in Kitchens	0.78	2.06	0.02	27.58
Mean PM 2.5 in Living Areas	0.25	0.66	0.00	10.10
Median PM 2.5 in Kitchens	0.33	1.73	0.00	27.05
Median PM 2.5 in Living Areas	0.13	0.56	0.00	9.42
95th Percentile PM 2.5 in Kitchens	2.50	4.69	0.01	56.57
95th Percentile PM 2.5 in Living Areas	0.75	1.80	0.00	17.18
Stove Type				
One Traditional Stove	0.26	0.44	0	1
One Improved Stove	0.01	0.08	0	1
One Clean Stove	0.20	0.40	0	1
Primary Stove is Traditional; Secondary Stove is Clean	0.14	0.35	0	1
Primary Stove is Improved; Secondary Stove is Traditional	0.00	0.04	0	1
Primary Stove is Improved; Secondary Stove is Clean	0.01	0.08	0	1
Primary Stove is Clean; Secondary Stove is Traditional	0.08	0.26	0	1
Both Primary and Secondary Stoves are Clean	0.04	0.20	0	1
Both Primary and Secondary Stoves are Traditional	0.26	0.44	0	1
Fuel Type				
Firewood	0.61	0.49	0	1
Crop Residue	0.09	0.28	0	1
Dung Cake	0.22	0.42	0	1
Charcoal	0.01	0.08	0	1
Coal	0.05	0.22	0	1
Kerosene	0.15	0.36	0	1
LPG	0.29	0.45	0	1

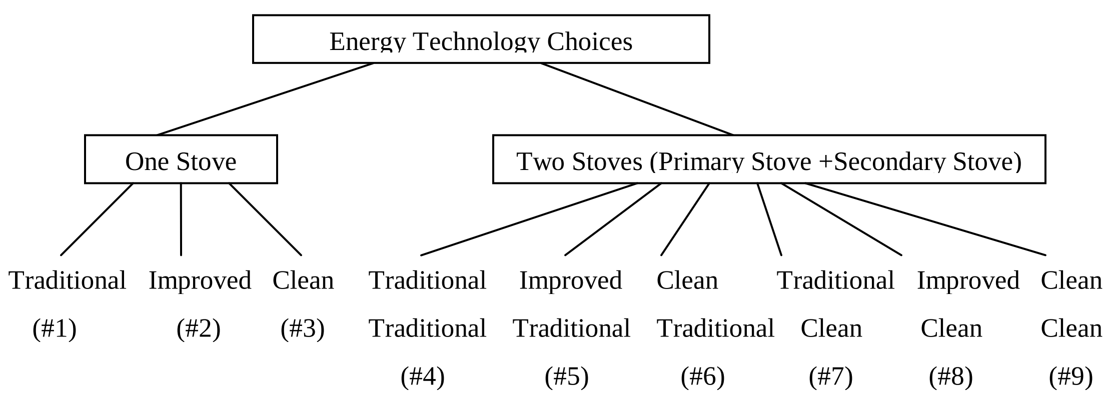
Fuel Quantity in Mega Joules (MJs)				
Firewood	70.52	88.68	0	460.75
Crop Residue	4.57	18.88	0	136.52
Dung Cake	8.82	21.99	0	133.11
Charcoal	0.32	4.23	0	71.67
Coal	2.46	14.75	0	225.26
Kerosene	1.27	3.83	0	28.44
LPG	0.95	3.43	0	23.12
Wall Materials				
Mud Wall	0.31	0.46	0	1
Non Mud Wall	0.69	0.46	0	1
Ventilation Condition				
Good	0.30	0.46	0	1
Moderate	0.42	0.49	0	1
Poor	0.28	0.45	0	1
Kitchen Location				
Separate Inside	0.25	0.43	0	1
External; Outside Door	0.12	0.32	0	1
External; Inside & Outside Door	0.19	0.39	0	1
Outdoor	0.12	0.32	0	1
Detached Enclosed	0.13	0.34	0	1
Living Room	0.19	0.39	0	1
Cooking Time	4.03	2.17	0	12
Household Size	5.09	2.13	1	15
Median Temperature ($^{\circ}$C)	20.65	4.57	9.43	30.49
Median Humidity (%)	63.91	10.31	31.00	87.50
State of Residence				
West Bengal	0.28	0.45	0	1
Madhya Pradesh	0.26	0.44	0	1
Tamil Nadu	0.19	0.40	0	1
Uttarakhand	0.26	0.44	0	1

Source: The HEED Survey.

The difference between traditional stoves and improved stoves is that improved stoves are generally more energy efficient and less polluting (especially the ones with a chimney) than traditional stoves. Clean stoves include LPG stoves, kerosene stoves, and biogas stoves (less than 2% in the HEED sample). Consequently, LPG, kerosene, and biogas are classified as clean fuels in this model. Thus, the stove-fuel combination is relatively simple: traditional stoves and improved stoves use dirty fuel and clean stoves use clean fuel.

Because very few household use more than two stoves, I only study those households who use no more than two cooking stoves. Furthermore, no households use improved stoves as the secondary cooking stove in the HEED sample. Therefore, the energy technology choice can be depicted as a nesting structure as shown in Figure 3-1. One choice is the number of stoves (1 or 2) and another choice is the type of stove (traditional, improved, or clean). Thus, there are a total of nine alternative choices.

Figure 3-1. Energy Technology Choices Related to Stove Type



Estimated Effects of the Energy Technology Choice on IAP

Regression results with the natural log of PM 2.5 concentrations in the kitchen as the dependent variables are presented in Table 3-2. Only 2% of observations have a mean PM 2.5 greater than 5 mg/m^3, as shown in Figure 3-2. Since these extreme values are rare and are likely

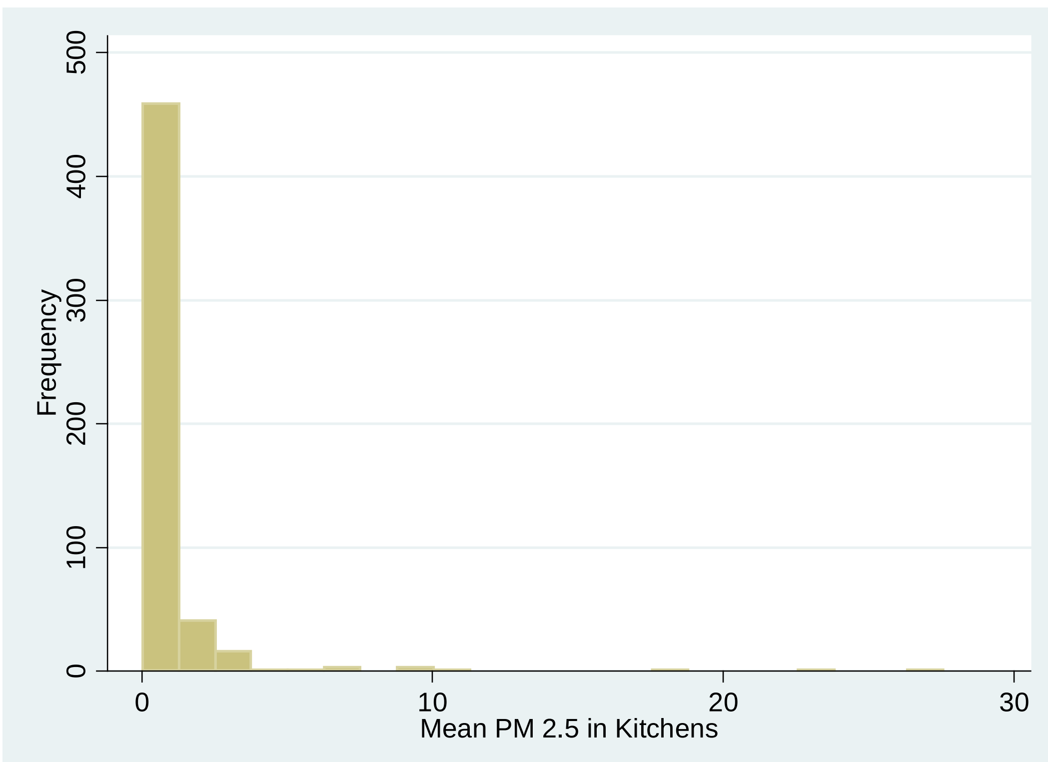
Table 3-2. Regression Results Explaining PM 2.5 Concentrations in Kitchens by Stove Type[a]

Regression Variable	Natural Log of Mean PM 2.5 Concentration		Natural Log of 95th Percentile PM 2.5 Concentration	
	(1)	(2)	(3)	(4)
Stove Type				
One Traditional Stove	-0.236+	-0.227	-0.129	-0.12
	[1.68]	[1.64]	[0.72]	[0.68]
One Improved Stove	-1.104+	-0.755	-1.398+	-1.028
	[1.86]	[1.28]	[1.85]	[1.36]
One Clean Stove	-1.423**	-1.230**	-1.811**	-1.583**
	[9.11]	[7.57]	[9.09]	[7.64]
Primary Stove is Traditional; Secondary Stove is Clean	-0.349*	-0.25	-0.504*	-0.388+
	[2.13]	[1.53]	[2.41]	[1.86]
Primary Stove is Improved; Secondary Stove is Traditional	-0.856	-0.862	0.137	0.222
	[0.85]	[0.87]	[0.11]	[0.18]
Primary Stove is Improved; Secondary Stove is Clean	-0.642	-0.394	-0.578	-0.302
	[1.09]	[0.67]	[0.77]	[0.40]
Primary Stove is Clean; Secondary Stove is Traditional	-1.126**	-0.958**	-1.305**	-1.106**
	[5.63]	[4.76]	[5.12]	[4.30]
Both Primary and Secondary Stoves are Clean	-1.380**	-1.303**	-1.805**	-1.706**
	[5.45]	[5.14]	[5.59]	[5.28]
Wall Materials				
Mud Wall	0.088	0.084	0.106	0.098
	[0.77]	[0.73]	[0.72]	[0.67]
Ventilation Condition				
Good Ventilation	-0.395**	-0.512**	-0.595**	-0.699**
	[3.22]	[3.77]	[3.80]	[4.03]
Moderate Ventilation	-0.172	-0.164	-0.366*	-0.333*
	[1.51]	[1.42]	[2.52]	[2.26]
Kitchen Location				
Separate Inside		-0.382*		-0.456*
		[2.58]		[2.42]
External; Outside Door		-0.15		-0.185
		[0.84]		[0.81]
External; Inside & Outside Door		-0.074		-0.287
		[0.43]		[1.32]
Outdoor		0.427*		0.475+
		[2.20]		[1.91]
Detached Enclosed		-0.027		-0.133
		[0.15]		[0.58]
Cooking Time	0.056*	0.061*	0.076*	0.084**
	[2.20]	[2.41]	[2.35]	[2.63]
Household Size	0.044+	0.049*	0.070*	0.075*

	[1.88]	[2.11]	[2.36]	[2.54]
Median Temperature	0.022	0.026	0.012	0.014
	[1.33]	[1.56]	[0.56]	[0.66]
Median Humidity	-0.001	-0.006	-0.002	-0.008
	[0.20]	[1.01]	[0.24]	[1.10]
State of Residence				
West Bengal	-0.181	-0.394*	-0.225	-0.450*
	[1.11]	[2.29]	[1.08]	[2.04]
Madhya Pradesh	-0.337	-0.430+	-0.500+	-0.477
	[1.63]	[1.88]	[1.90]	[1.63]
Tamil Nadu	-0.991**	-1.130**	-1.321**	-1.441**
	[3.89]	[4.34]	[4.07]	[4.34]
Constant	-1.105*	-0.783	0.273	0.743
	[2.16]	[1.49]	[0.42]	[1.10]
Observations	504	504	504	504
***R^2* statistic**	0.374	0.397	0.405	0.425

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

Figure 3-2. Distribution of Mean PM 2.5 Concentrations in Kitchens



the result of measurement errors or certain unobservable conditions, I exclude them from the regressions. Columns (1) and (2) use the log of mean PM 2.5 concentrations as the dependent variable and Columns (3) and (4) use the log of the 95th percentile PM 2.5 concentration as the dependent variable.

Because kitchen locations correlate with energy technology and ventilation conditions, for example, clean stoves are usually used indoors and outdoor kitchens usually have better ventilation conditions, it becomes difficult to disentangle the effects of kitchen location from the effects of energy technology and ventilation conditions. To have a better idea of the effects of kitchen location, Columns (1) and (3) report the regression results without these variables and Columns (2) and (4) report the results including kitchen location variables. By including kitchen location variables, the effects of energy technologies are generally reduced and good ventilation becomes more important. Since kitchen location variables are jointly significant with an F test statistic of $F(4, 480) = 4.37$ corresponding to a *p*-value of 0.0018, Columns (2) and (4) are preferred regressions.

The effects of having two traditional stoves, a non-mud wall (e.g., thatch, wood, stone, or brick), poor ventilation, a kitchen in the living room, and residence in Uttarakhand are included in the constant term.

To verify that concentration effects are the same for rural and urban households, a Chow test is conducted using the specification of Column (2). The Chow test which allows all coefficients to differ between the two sets of households has an F-statistic $F(23, 485) = 1.325$ with a corresponding *p*-value of 0.145, so I cannot reject the hypothesis that the coefficients are the same for rural and urban households. In addition, Tamil Nadu appears to have significantly lower IAP concentrations compared to other states. The fact that the ventilation data were collected by a different survey team in Tamil Nadu than other states raises concerns of survey bias that might interact with the estimation of other coefficient. The presence of bias associated with a survey team effect in Tamil Nadu compared to other states is investigated with a Chow test. The test of common coefficients among all states, aside from a state shift effect, compared to different coefficients for Tamil Nadu generated an F-statistic of $F(23, 458) = 1.145$ with a corresponding *p*-value of 0.287. Thus, the hypothesis that concentration effects for Tamil Nadu are the same as for the other three states aside from a shift term cannot be rejected.

Because the dependent variables in the Table 3-2 regressions are in log form, the raw parameter estimates do not provide direct evidence of the magnitude and percentage effects of the various explanatory variables. For this purpose, Table 3-3 converts the estimated equations into estimates of the magnitude and percentage change in IAP caused by each of the individual explanatory variables. Because the variables have interactive effects, this is done for each explanatory variable holding all other right hand side variables at their overall sample averages.

The results show that having a clean stove as the primary stove significantly reduces PM 2.5 concentrations in kitchens. If an average household switches from using traditional stoves for both the primary stove and secondary stove to only using one clean stove, the PM 2.5 mean concentration is reduced by 0.543 mg/m^3 or 71% and the PM 2.5 95^{th} percentile concentrations is reduced by 2.234 mg/m^3 or 79%. Having a clean stove as the secondary stove, while using a traditional stove or improved stove as the primary stove, also shows improvement of PM 2.5 concentrations. However, this estimate is not statistically significant. This implies that partial fuel switching with regard to the secondary stove may not have significant impacts on household IAP levels. These results imply that if households use clean fuels only for making tea, but still use traditional biomass for cooking, then the household IAP level does not change much.

Having an improved stove is also estimated to cause substantial reductions in PM 2.5 concentrations. If an average household with both primary and secondary traditional stoves

Table 3-3. Change in PM 2.5 Concentrations Associated with Energy Technology Choice[a]

Variable	PM 2.5 Mean Concentrations		PM 2.5 95th Percentile Concentrations	
	Absolute Change (mg/m3)	**Percentage Change**	**Absolute change (mg/m3)**	**Percentage Change**
Stove Type				
One Traditional Stove	-0.156	-20%	-0.318	-11%
One Improved Stove	-0.406	-53%	-1.806	-64%
One Clean Stove	-0.543	-71%	-2.234	-79%
Primary Stove is Traditional; Secondary Stove is Clean	-0.170	-22%	-0.904	-32%
Primary Stove is Improved; Secondary Stove is Traditional	-0.443	-58%	0.699	25%
Primary Stove is Improved; Secondary Stove is Clean	-0.250	-33%	-0.733	-26%
Primary Stove is Clean; Secondary Stove is Traditional	-0.473	-62%	-1.881	-67%
Both Primary and Secondary Stoves are Clean	-0.559	-73%	-2.301	-82%
Wall materials				
Mud wall	0.044	9%	0.201	10%
Ventilation condition				
Good ventilation	-0.298	-40%	-1.578	-50%
Moderate ventilation	-0.112	-15%	-0.888	-28%
Kitchen location				
Separate Inside	-0.171	-32%	-0.743	-37%
External, Outside Door	-0.075	-14%	-0.342	-17%
External, Inside & Outside Door	-0.038	-7%	-0.506	-25%
Outdoor	0.287	53%	1.233	61%
Detached Enclosed	-0.007	-1%	-0.253	-12%
Cooking time	0.017	6%	0.181	9%
Household Size	0.013	5%	0.161	8%
Median Temperature	0.007	3%	0.029	1%
Median Humidity	-0.002	-1%	-0.016	-1%
State of Residence				
West Bengal	-0.216	-33%	-1.048	-36%
Madhya Pradesh	-0.232	-35%	-1.097	-38%
Tamil Nadu	-0.449	-68%	-2.207	-76%

[a] Changes compare the effects of the two alternative states of the subject variable holding all other variables at their average levels across all households in the sample.

switches the primary stove to an improved stove, the PM 2.5 mean concentration is estimated to decline by 0.443 mg/m^3 or 58%. However, this result is not statistically significant. This may be due to the small sample size of households with improved stoves (only nine households or 1.5% of households in the sample use improved stoves and two of them had missing data).

In addition, ventilation conditions play a significant role. This variable represents one of three categories (good, moderate, and poor) as rated by observers. Using subjectively rated ventilation variables may introduce bias because systematic error may be introduced in the rating depending on how observers define good, moderate, and poor ventilation. Although more objective measurements (e.g., number of windows/vents/doors, whether windows/doors are open during cooking, whether there are open eves between the walls and roof) are available, including these variables increases the number of regressors, reduces the clarity of parameter estimators, and complicates interpretation. To test whether the joint use of these additional variables is merited, an F test is used. The associated F-statistic is $F(5, 476) = 1.09$ corresponding to a *p*-value of 0.63, which reveals that these variables are not jointly statistically significant.[3] Alternatively, an F test for removing the subjectively rated ventilation conditions from the regression given that the objective measurements are included generates an F-statistic of $F(2,476) = 4.93$ corresponding to a *p*-value of 0.008, which reveals that the rated ventilation-condition variables are statistically significant and removing them would significantly reduce the model's goodness of fit. Therefore, I used the rated ventilation condition as the ventilation indicator. As Table 3-3 shows, if an average household can improve the ventilation condition from poor to good, the PM 2.5 mean concentration is reduced by 0.298 mg/m^3 or 40%.

In terms of wall materials, a study in Bangladesh (Dasgupta, et al, 2004a) finds that, in most areas, the soil has low sand content and mud walls and floors are frequently re-coated with fresh mud to prevent cracking. This creates an effective seal that permits almost no ventilation in comparison with other building materials. If cooking is done inside the house, the sealing effect

[3] Added variables included five dummies: whether there is a window in kitchen, whether the window is open during cooking, whether there is a door in the kitchen, whether the door is open during cooking, and whether there is an open eve between the walls and roof.

of mud walls increases the PM 2.5 concentrations. The regression results have the expected sign, but the coefficients are not statistically significant nor are magnitudes large.

Kitchen location also plays a significant role. Having a separate kitchen inside the house significantly reduces IAP concentrations while having an outdoor kitchen significantly increases IAP concentrations compared to cases where the kitchen is in the living area. This may seem counter-intuitive for outdoor kitchens because they have better ventilation. Since the outdoor kitchen is correlated with both stove type (clean stoves are almost never used outdoors) and ventilation conditions, and the regression controls for both effects, this result may be explained by the use of dirtier traditional fuels such as crop residue in outdoor kitchens.

The results show that longer cooking times and a greater number of people also increase PM 2.5 concentrations. These results are as expected because more people require more fuel use to cook more food, and increased cooking time means longer combustion time. An additional hour of cooking time and one more person in the household have a similar effect on PM 2.5 mean concentrations. Both increase the PM 2.5 mean concentrations by 5-6%. In addition, although neither median temperature nor median humidity have a significant impact on IAP concentrations, they are jointly statistically significant, which suggests the need to control for these two factors.

Since the post-monitoring questionnaire also includes fuel quantity information for both primary and secondary stoves, I attempted to include such information in the regressions in Table 3-2, but did not get sensible results (and are thus not reported). The survey team measured the amount of fuel use in terms of kilograms (kg) of weight or milliliters (ml) of volume (for kerosene) for both primary and secondary stoves during the 24-hour monitoring period. The survey team asked the household member, preferably the person who had cooked during the monitoring period, to approximate the amount of fuel used during the period. Then it was measured by a weighing balance carried by the team. For kerosene, the team calculated the amount of liters left in the kerosene can. For LPG, the team calculated the monthly weight change of the cylinder divided by the number of days per month. The poor results for regressions including fuel quantity are likely explained by the short intervals of fuel use, the wide variation of measurement methods, and the fact that more than half of the observations had missing values in the fuel quantity data.

Estimated Effects of Fuel Type on IAP

One problem with focusing on stove types alone is that the polluting difference between dirty fuel types and clean fuel types is ignored. For example, crop residues generally emit more smoke than firewood during combustion and LPG is considered cleaner than kerosene. To examine how types of cooking fuel affect IAP levels, the type of fuel is used to model energy technology in this section. Because multiple types of cooking fuels are commonly used together, the type of fuel used is not exclusive.

In addition, because NCAER data includes the amount of fuel used by fuel type over the last month, I am able to use this information to complement the missing fuel quantities in the post-monitoring data. Therefore, the sample size is large enough to estimate the effect of the amount of fuel used on IAP levels. Thus, the general model specification includes both a shift term if a particular fuel was part of the mix of fuels used, and continuous terms representing the amount of each fuel used.

Regression results with the natural log of PM 2.5 concentrations in kitchens at the mean and 95th percentile as dependent variables are presented in Table 3-4. Again, outliers with a mean PM 2.5 greater than 5 mg/m^3 are excluded for reasons given above. Again, a Chow test for

Table 3-4. Regression Results Explaining PM 2.5 Concentrations in Kitchens by Fuel Type[a]

Regression Variable	Natural Log of Mean of PM 2.5 Concentration			Natural Log of 95th Percentile of PM 2.5 Concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
Fuel Type						
Firewood	0.720**	0.770**	0.640**	0.942**	1.018**	0.828**
	[4.60]	[4.87]	[5.09]	[4.70]	[5.01]	[5.15]
Crop Residue	0.910*	0.951*	0.924**	1.136*	1.179*	1.052**
	[2.48]	[2.57]	[4.33]	[2.41]	[2.48]	[3.85]
Dung Cake	0.046	-0.042	0.273*	-0.027	-0.147	0.287
	[0.21]	[0.18]	[1.99]	[0.10]	[0.50]	[1.63]
Charcoal	2.058		2.511**	-0.698		2.702**
	[0.78]		[4.25]	[0.21]		[3.58]
Coal	0.627		0.691**	0.756		0.791**
	[1.48]		[2.92]	[1.40]		[2.61]
Kerosene	-0.074	-0.025	0.068	-0.18	-0.152	-0.012
	[0.34]	[0.11]	[0.45]	[0.63]	[0.52]	[0.06]
LPG	-0.381*	-0.355*	-0.243+	-0.638**	-0.610**	-0.428**
	[2.55]	[2.33]	[1.91]	[3.33]	[3.12]	[2.62]
Mega Joules by Fuel Type						
Firewood	0.0002	0.0004		0.0002	0.0004	
	[0.24]	[0.41]		[0.20]	[0.38]	
Crop Residue	0.003	0.003		0.001	0.001	
	[0.60]	[0.66]		[0.13]	[0.18]	
Dung Cake	0.004	0.006		0.007	0.008+	
	[1.20]	[1.53]		[1.37]	[1.74]	
Charcoal	0.011			0.059		
	[0.27]			[1.06]		
Coal	0.0001			0.003		
	[0.02]			[0.39]		
Kerosene	0.021	0.021		0.025	0.027	
	[1.09]	[1.10]		[1.00]	[1.07]	
LPG	0.027+	0.027+		0.046*	0.046*	
	[1.83]	[1.82]		[2.44]	[2.48]	
Wall Materials						
Mud Wall	0.129	0.089	0.12	0.191	0.131	0.153
	[1.01]	[0.68]	[1.02]	[1.16]	[0.77]	[1.02]
Ventilation Condition						
Good	-0.531**	-0.521**	-0.498**	-0.749**	-0.722**	-0.715**
	[3.65]	[3.53]	[3.62]	[4.02]	[3.81]	[4.06]
Moderate	-0.239+	-0.217+	-0.217+	-0.425**	-0.414*	-0.396**
	[1.92]	[1.71]	[1.85]	[2.67]	[2.54]	[2.65]
Kitchen Location						
Separate Inside	-0.380*	-0.365*	-0.373*	-0.420*	-0.424*	-0.439*
	[2.45]	[2.30]	[2.49]	[2.11]	[2.08]	[2.30]
External: Outside Door	-0.038	-0.034	-0.091	-0.02	-0.036	-0.08
	[0.20]	[0.18]	[0.51]	[0.08]	[0.15]	[0.35]
External; Inside & Outside Door	-0.049	0.073	-0.06	-0.17	-0.091	-0.227

	[0.27]	[0.38]	[0.35]	[0.72]	[0.37]	[1.03]
Outdoor	0.471*	0.510*	0.518**	0.580*	0.591*	0.639*
	[2.33]	[2.49]	[2.67]	[2.24]	[2.25]	[2.57]
Detached Enclosed	-0.047	-0.007	0.044	-0.126	-0.091	-0.006
	[0.24]	[0.03]	[0.24]	[0.51]	[0.36]	[0.02]
Cooking Time	0.047	0.045	0.067**	0.068+	0.061	0.091**
	[1.60]	[1.51]	[2.62]	[1.79]	[1.59]	[2.77]
Household Size	0.058*	0.053*	0.067**	0.081*	0.077*	0.094**
	[2.27]	[2.07]	[2.85]	[2.49]	[2.33]	[3.13]
Median Temperature	0.033+	0.03	0.030+	0.022	0.019	0.018
	[1.78]	[1.59]	[1.74]	[0.91]	[0.79]	[0.83]
Median Humidity	-0.007	-0.006	-0.006	-0.008	-0.008	-0.009
	[1.09]	[0.97]	[1.07]	[1.09]	[0.98]	[1.22]
State of Residence						
West Bengal	-0.422*	-0.390*	-0.448**	-0.531*	-0.493*	-0.549*
	[2.29]	[2.07]	[2.61]	[2.25]	[2.04]	[2.50]
Madhya Pradesh	-0.618*	-0.640*	-0.571*	-0.728*	-0.710*	-0.647*
	[2.32]	[2.37]	[2.36]	[2.13]	[2.05]	[2.10]
Tamil Nadu	-1.236**	-1.204**	-1.225**	-1.549**	-1.511**	-1.549**
	[4.38]	[4.18]	[4.72]	[4.28]	[4.08]	[4.67]
Constant	-1.865**	-1.926**	-1.898**	-0.551	-0.613	-0.511
	[3.15]	[3.16]	[3.43]	[0.73]	[0.78]	[0.72]
Observations	451	431	502	451	431	502
***R^2* statistic**	0.405	0.400	0.389	0.431	0.430	0.414

[a] The absolute values of *t*-statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

whether the Tamil Nadu data follow the same model as other states is not rejected at standard significance levels with an F statistic of $F(23,456) = 1.030$, which has a *p*-value of 0.425. The effects of non-mud wall construction, poor ventilation, a kitchen in the living room, and residence in Uttarakhand are included in the constant term. Columns (1), (2), (4) and (5) include both fuel type and amount of fuel measured in mega joules (MJ) by fuel type.

Columns (2) and (5) exclude households that use charcoal or coal. Charcoal and coal have very high coefficients although they are not statistically significant. These results are somewhat surprising because charcoal and coal are usually believed to be cleaner than traditional biomass. Both the surprising signs and significance of these fuels may be due to the small number of households using these two types of fuel and/or any special circumstances associated with these households that are not controlled in the data. For example, if households using coal are closer to a coal mine, outdoor air pollution may be high, which also affects IAP levels. Columns (2) and (5) exclude households that use charcoal or coal in order to exclude this potential bias. The coefficients for other variables change only slightly.

Coefficients for the amount of fuel used by fuel type in Columns (1), (2), (4), and (5) are all positive as expected. Surprisingly, however, the coefficients for the amount of fuel consumption have little significance whereas many of the coefficients on shift terms are highly significant. Using an F test with an F-statistic of $F(7, 421) = 0.88$ corresponding to a p-value of 0.5194 reveals that the category of variables representing maga joules used by fuel type is not jointly statistically significant. This result is counterintuitive for a fuel use model where each incremental use of a particular fuel adds to IAP from a starting point where no use of a fuel causes no IAP.

One interpretation may be that the most polluting part of cooking is starting the fire. Once the fire is started, the amount of fuel used has relatively small effects on IAP levels. This seems particularly true for traditional biomass fuels where the estimated coefficients for the amount of biomass fuel used are much smaller than the ones for clean fuels. The implication of the results is that the mix of fuel types in use represents primarily the energy technology choice and that the amounts of fuels used are determined consequentially.

Columns (3) and (6) thus reduce the model to the essential implications of the fuel mix as a representation of the technology choice and appear to be the preferred specifications. These results should be interpreted with caution. Even though the estimated equation suggests that an initial minute addition of a particular fuel type to the fuel mix has a discrete effect on IAP, the set of active fuel type indicators are more properly interpreted as defining the cooking technology.

Estimates in columns (3) and (6) of Table 3-4 imply that including firewood or crop residue in the fuel mix has a significant positive effect on the PM 2.5 concentrations. In particular, crop residue has a higher coefficient than firewood, which suggests that crop residue is more polluting than firewood. Including LPG in the fuel mix causes a statistically significant reduction of PM 2.5 concentrations. Although kerosene also has a negative impact, it is not statistically significant.

Similar to the structure in Table 3-3, using the estimates in Columns (3) and (5) in Table 3-4, Table 3-5 shows how each explanatory variable affects PM 2.5 concentrations for an average household holding all other variables at their overall sample average. If an average household adds firewood to the fuel mix, the PM 2.5 mean concentrations increase by 0.355 mg/m^3 or 90%. If an average household adds crop residue to the fuel mix, the increase of PM 2.5 mean concentrations will be even higher, 152% of the original level. By adding LPG to the fuel mix, an average household can reduce the PM 2.5 mean concentrations by 0.137 mg/m^3 or 22%.

Other variables such as ventilation condition, kitchen location, cooking time, and number of people in the household continue to have significant estimated impacts on IAP levels. Their magnitudes are only slightly different than in the results in Table 3-3.

Predicting Typical Household IAP Exposure Levels

The post-monitoring data measures household energy use during the 24-hour IAP monitoring period, while the NCAER data measures household energy use during the year. Thus, by smoothing the random day-to-day variations, the NCAER data should reflect household energy use characteristics better than the post-monitoring data. Since the two data sets share most variables that measure household energy use characteristics, the IAP regression results from the post-monitoring data can be used to predict typical household IAP exposure levels using the NCAER data.

Table 3-5. Change in PM 2.5 Concentrations Associated with Fuel Type[a]

Variable	PM 2.5 Mean Concentrations		PM 2.5 95th Percentile Concentrations	
	Absolute Change (mg/m3)	Percentage Change	Absolute change (mg/m3)	Percentage Change
Fuel Type				
Firewood	0.355	90%	1.832	129%
Crop Residue	0.806	152%	3.754	186%
Dung Cake	0.151	31%	0.595	33%
Charcoal	6.038	1132%	28.310	1391%
Coal	0.540	100%	2.492	121%
Kerosene	0.040	7%	-0.026	-1%
LPG	-0.137	-22%	-0.851	-35%
Wall materials				
Mud Wall	0.065	13%	0.323	17%
Ventilation Condition				
Good Ventilation	-0.291	-39%	-1.602	-51%
Moderate Ventilation	-0.145	-20%	-1.026	-33%
Kitchen Location				
Separate Inside	-0.169	-31%	-0.727	-36%
External, Outside Door	-0.047	-9%	-0.157	-8%
External; Inside & Outside Door	-0.032	-6%	-0.416	-20%
Outdoor	0.369	68%	1.831	89%
Detached Enclosed	0.024	4%	-0.012	-1%
Cooking time	0.038	7%	0.197	10%
Household Size	0.038	7%	0.204	10%
Median temperature	0.017	3%	0.038	2%
Median humidity	-0.003	-1%	-0.019	-1%
State of Residence				
West Bengal	-0.182	-36%	-0.748	-42%
Madhya Pradesh	-0.219	-44%	-0.843	-48%
Tamil Nadu	-0.355	-71%	-1.394	-79%

[a] The raw magnitude and percentage change in IAP between the dichotomous states of each explanatory variable is evaluated holding all other variables at their overall sample average..

The IAP regressions in Table 3-2 and Table 3-4 give two ways to model household energy technology. An F test with an F test statistic of F (1, 478) = 1.2999 corresponding to a *p*-value of 0.75 does not imply a statistically significant difference between the two models. I use the regression results that focus on stove type to predict typical household IAP exposure levels for the following reasons: (1) stove choices are usually more stable than fuel choices because a stove is a capital cost while fuel is a variable cost; (2) stove choices capture the different IAP impacts of using primary and secondary stoves; (3) the regressions focusing on fuel types show that dirty fuels have relatively similar IAP impacts and clean fuels have relatively similar IAP impacts, implying that the difference between dirty fuels and clean fuels is largely captured by stove choices; and (4) the model focusing on stove types has a slightly higher R^2 statistic than the model focusing on fuel types.

Table 3-6 shows the comparison of stove types between the post-monitoring data and the NCAER data. Pearson's chi-square test with $\chi^2(72) = 277.2125$ corresponding to a *p*-value less than 0.001 rejects the hypothesis that the two data sets are independent. Cramer's ϕ' statistic is 0.411 and the correlation of the two data sets is 0.417.

Table 3-6. Comparison of Stove Types in Post-Monitoring Data and NCAER Data

Stove Types in Post-Monitoring Data	Stove Types in NCAER data									
	Dirty Only	Improved Only	Clean Only	Dirty Dirty	Improved Dirty	Clean Dirty	Dirty Clean	Improved Clean	Clean Clean	Total
Dirty Only	116	1	1	22	2	5	28	0	6	181
Improved Only	0	1	0	1	0	1	1	0	0	4
Clean Only	4	0	55	1	0	34	5	0	15	114
Dirty Dirty	99	0	1	17	0	0	31	1	0	149
Improved Dirty	1	0	0	0	0	1	0	1	0	3
Clean Dirty	0	0	2	0	0	25	14	0	5	46
Dirty Clean	11	0	1	2	0	5	60	3	0	82
Improved Clean	0	0	0	0	0	1	2	0	0	3
Clean Clean	1	0	6	0	0	1	4	0	10	22
Total	232	2	66	43	2	73	145	5	36	604

The prediction equation for the PM 2.5 mean in the NCAER data using the regression results in Table 3-2, Column (2), is

$$\ln \overline{Y} = X\hat{\beta}$$

$$\overline{Y} = e^{\ln \overline{Y} + \hat{\sigma}_e^2/2}$$

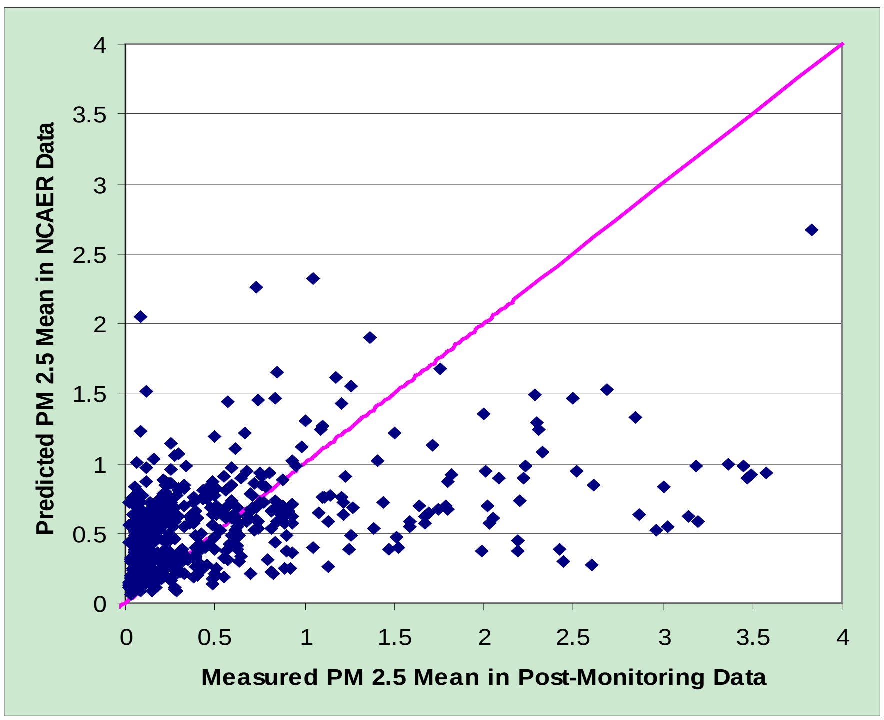
where $\overline{Y}$ is the predicted mean of PM 2.5 concentration in the NCAER data, X represents the vector of independent variable values from the NCAER data, $\hat{\beta}$ is a vector of the corresponding estimated coefficients shown in Column (2) of Table 3-2, and $\hat{\sigma}_e^2$ is the variance of residuals from the regression.

The predicted PM 2.5 mean values in the NCAER data and how they compare with the measured PM 2.5 mean values are illustrated in Table 3-7, Figure 3-3, and Figure 3-4. The correlation between the predicted and measured PM 2.5 mean values is 0.47, which is considerably higher than the R^2 statistics in Table 3-2. The major difference between the maximum values is due to the fact that households reported as using only one dirty stove and an external kitchen with outside door in the post-monitoring data were reported as using a dirty primary stove, clean secondary stove, and detached enclosed kitchen in the NCAER data (see Table 3-6). Comparison of the natural log of predicted and measured PM 2.5 means in Figure 3-4 is better than the comparison without natural logs in Figure 3-3. This occurs because the dependent variable I use in the IAP regression is in the natural log form and the natural log form has a better goodness of fit. The comparison in Figure 3-4 also shows that the predicted PM 2.5 means tend to be slightly lower than the measured PM 2.5 means as the slope is less than 1. This implies that the predicted values in general are lower than the measured values. An explanation of this result is that more households reported using only one clean stove in the post monitoring data than in the NCAER data.

Table 3-7. Comparison of Summary Statistics of Predicted and Measured PM 2.5 Means

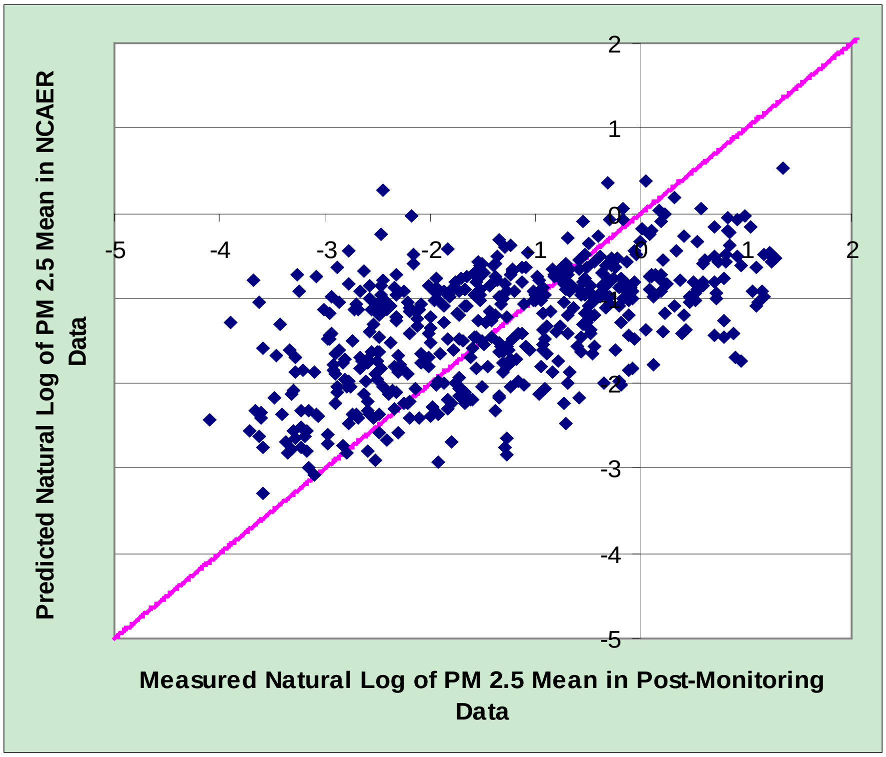
Variable (mg/m3)	Observations	Mean	Standard Deviation	Minimum	Maximum
Predicted PM 2.5 Mean	515	0.5384	0.3591	0.0579	2.6688
Measured PM 2.5 Mean	515	0.5511	0.7138	0.0165	3.8353
Natural Log of Predicted PM 2.5 Mean	515	-1.2938	0.6964	-3.3032	0.5278
Natural Log of Measured PM 2.5 Mean	515	-1.3155	1.2383	-4.1017	1.3442

Figure 3-3. Comparison of Predicted and Measured PM 2.5 Means



Similarly, the coefficients in Table 3-2, Column (4), can be used to predict PM 2.5 95th percentile values in the NCAER data. The comparisons of predicted and measured PM 2.5 95th percentile values are presented in Table 3-8, Figure 3-5, and Figure 3-6. Similar patterns emerge as discussed for PM 2.5 means. The correlation between the predicted and measured PM 2.5 95th percentile values is 0.47, which is somewhat higher than the R^2 statistics in Table 3-2.

Figure 3-4. Comparison of Predicted and Measured Logs of PM 2.5 Means



Although direct IAP monitoring can be expected to yield the most accurate IAP levels for a short period such as 24 hours, it may not yield the best representation of typical IAP levels that households face over longer periods due to day-to-day variations. The HEED survey includes two data sets that have similar variables but one data set reflects 24-hour monitoring of cooking practices and the other measures year-long cooking practices. Thus, the latter data set provides the opportunity to predict typical household IAP levels by smoothing random day-to-day variations. Comparing the reported stove types in the two sets, I find that although they have a significant positive correlation of 0.41, they differ for a number of households. For example, 34 households reported the use of a clean stove during the monitoring period, but reported use of both a clean stove and a traditional stove during the year. Thus, assuming the NCAER data reflects household energy use characteristics better than the post-monitoring data, the predicted household IAP exposure levels using the NCAER data represents more typical IAPs levels to which households are exposed.

Table 3-8. Comparison of Summary Statistics of Predicted and Measured PM 2.5 95th Percentile Values

Variable (mg/m3)	Observations	Mean	Standard Deviation	Minimum	Maximum
Predicted PM 2.5 95th Percentile	515	2.3372	2.1748	0.0898	15.0567
Measured PM 2.5 95th Percentile	515	2.0780	3.1186	0.0148	21.0882
Natural Log of Predicted PM 2.5 95th Percentile	515	-0.2922	0.9525	-3.1498	1.9720
Natural Log of Measured PM 2.5 95th Percentile	515	-0.3313	1.6151	-4.2129	3.0487

Figure 3-5. Comparison of Predicted and Measured PM 2.5 95th Percentile Values

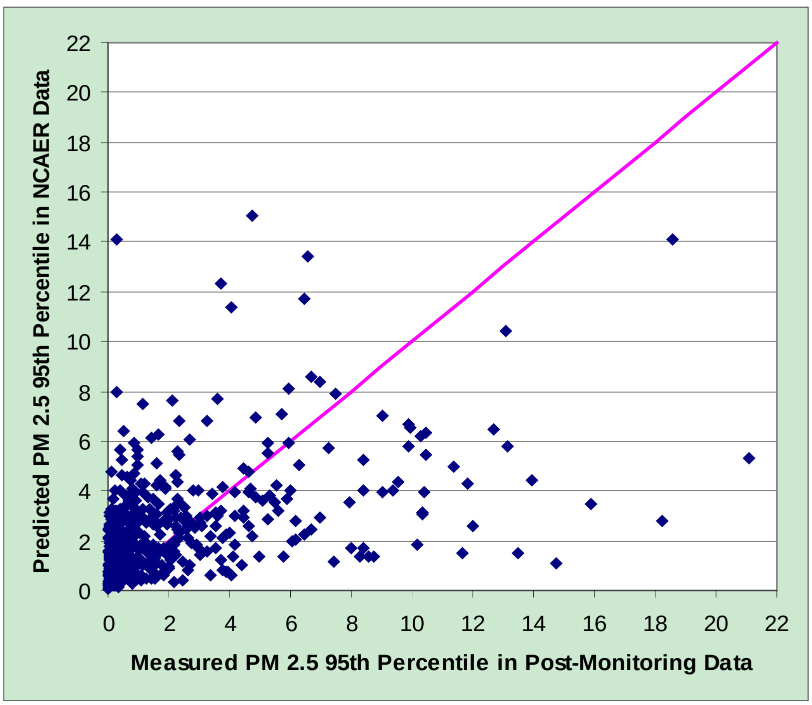
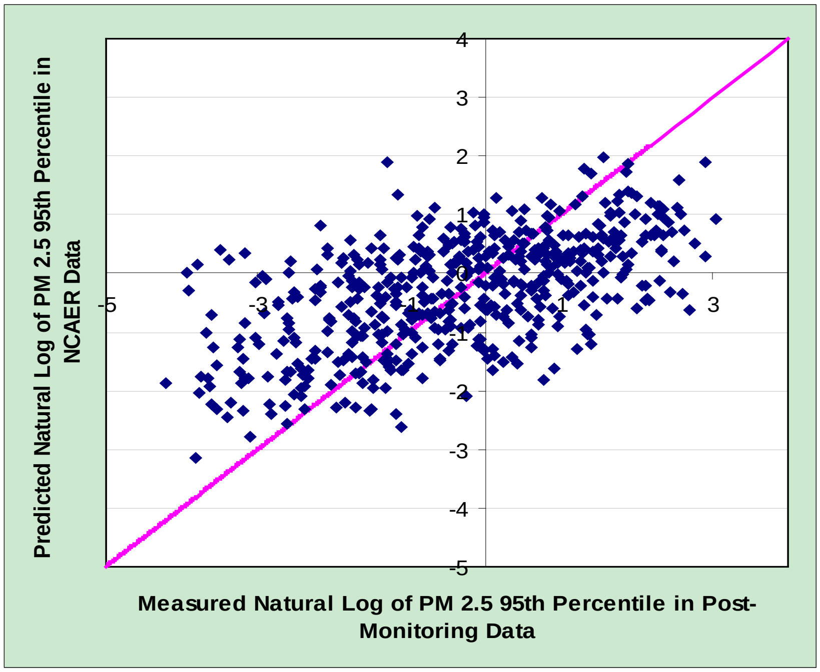


Figure 3-6. **Comparison of Predicted and Measured Logs of PM 2.5 95th Percentile Values**



Conclusions

In this chapter, I have analyzed the determinants of IAP and household energy technology choices. Two ways were used to model household energy technology: one focusing on stove types and the other focusing on fuel types. Estimation with one approach or the other rather than in a model with joint effects is dictated by the availability of data in the post-monitoring and NCAER surveys. I find no statistically significant differences between the two approaches in terms of the data fitting. However, focusing on stove types gives several advantages over focusing on fuel types. For example, stove choices are usually more stable than fuel choices and thus subject to less noise. Using OLS regression analysis, I reach the following important findings.

- Having a clean stove as the primary stove significantly reduces PM 2.5 concentrations in kitchens. If an average household switches from using both a primary traditional stove and a secondary traditional stove to using only one clean stove, the PM 2.5 mean concentration will be reduced by 71%.

- Having a clean stove as the secondary stove is not statistically significant in reducing PM 2.5 concentrations.
- Having an improved stove that burns traditional fuel can potentially reduce PM 2.5 concentrations considerably as well. However, due to the small number of households using an improved stove, statistical significance for this effect could not be found.
- Ventilation conditions play a significant role. If an average household can improve the ventilation condition from poor to good, the PM 2.5 mean concentrations are reduced by 40%.
- Kitchen location, cooking time, and number of people also play important roles.
- Amount of fuel use does not have significance in determining PM 2.5 concentrations when fuel types and other factors are controlled, probably because starting the fire is the most polluting part of the cooking process.

Finally, results from the IAP regressions can be used to construct an IAP index. This IAP index can then be used to predict typical household IAP exposure levels in the HEED data. I use the predicted typical household IAP exposure levels to analyze health impacts from IAP in the next chapter.

Chapter 4. Health Impacts from Exposure to Indoor Air Pollution

Introduction

Indoor air pollution from traditional biomass fuel use in household stoves is a risk factor for several important diseases. Five of the air pollution related diseases – ischaemic heart disease, acute lower respiratory infections (ALRI), chronic obstructive pulmonary disease, tuberculosis, and cancers of the respiratory tract – are among the ten leading causes of death globally (Murray and Lopez 1997). In addition to contributing to respiratory diseases, exposure to cooking smoke seems to cause or exacerbate eye problems such as cataracts (WHO, 2002), harm newborns (Barnes et al, 1994), and reduce birth weight (Boy et al, 2002). Table 4-1 summarizes the status of evidence on the health effects of IAP. Several studies that quantitatively assess the relationship between exposure to household biomass smoke and ALRI in young children in developing countries have reported wide-ranging odds ratios ranging from 2 to 10 (Smith, et al, 2000). However, as discussed in Chapter 1, these findings are only suggestive because of the problem of limited data and failure to control for many other risk factors. More recently, Dherani et al (2008) conducted a meta-analysis of pneumonia risk from IAP in children aged under five years. Out of 5,317 reviewed studies, 24 were selected for the meta-analysis. Despite heterogeneity and evidence of publication bias, Dherani et al (2008) were able to provide sufficient consistency to conclude that risk of pneumonia in young children is increased by exposure to unprocessed solid fuels by a factor of 1.8. However, as few studies directly measure IAP, this meta-analysis was not able to further examine how IAP intensity affects health. In this chapter, I use the predicted typical household IAP exposure levels from Chapter 3 to analyze how IAP affects health.

Table 4-1. Summary of the Status of Evidence on the Health Effects of IAP

Health Outcome	Nature and Extent of Evidence
ALRI (children under 5)[a] COPD (adults)[b] Lung cancer	10-20+ studies from developing countries; fairly consistent results across studies, but confounding is not dealt with in many studies; supported by studies of ambient air pollution and environmental tobacco smoke (ETS) and to some extent by animal studies.
Cancer of nasopharynx and larynx Cataracts Tuberculosis	2-3 studies from developing countries; consistent results across studies; supported by evidence from smoking and animal studies.
Low birth weight Perinatal mortality	2-3 studies from developing countries; supported by evidence from ambient air pollution and ETS.
Acute otitis media Cardiovascular disease	No studies from developing counties, but an association may be expected from studies of ambient air pollution and studies of wood smoke in developed countries.
Asthma	Several studies from developing countries, but results are inconsistent; some support from studies of ambient air pollution, but results are also inconsistent.

[a] ALRI refers to acute lower respiratory infections.
[b] COPD refers to chronic obstructive pulmonary disease.
Source: Schirnding et al (2000), WHO (2002), Desai et al (2004).

The Estimated Model

The health outcome in the HEED survey data includes objective measurement of lung function reported by doctors in the survey team as well as self-reported respiratory symptoms, diagnosed diseases, and measured weight and height. Common logic suggests that higher IAP exposure would have higher incidence of disease. The two are indeed positively correlated. However, this positive correlation does not prove the causal relationship that higher IAP exposure causes higher incidence of disease. Because poor households usually cannot afford clean cooking fuels, they are more likely to be exposed to high IAP. But the poor are also more likely to have poor health for other reasons such as poor nutrition and poor medical care. To quantify precisely the relationship between exposure to IAP and incidence of disease, I extend typical models by using both IV estimation techniques and household-level fixed effects proposed by Pitt, et al (2006).

In Pitt et al's paper on how cooking time affects respiratory illness symptoms among adults, one concern is that cooking time may be correlated with unmeasured household and individual-specific health variables. To eliminate household unobservables, a household fixed-effects procedure was used. To deal with the problems of possible endogeneity of cooking time and the measurement error issue that cooking time varies from day-to-day, an instrumental variables procedure was implemented. A similar approach is adopted here as follows.

The basic estimation equation can be written as

$$h_{ij} = \beta_0 + \beta_1 T_{ij}^k P_j^k + \beta_A A_{ij} + \beta_S S_j + \mu_j + \varepsilon_{ij}$$

where h_{ij} is the health outcome (e.g., measured lung capacity or the incidence of respiratory symptoms) for individual *i* in household $j; T_{ij}^k$ is a dummy variable that indicates whether individual *i* is typically in the kitchen when there is a stove or fire burning; P_j^k is the PM 2.5 concentration in the kitchen during cooking time; A_{ij} is a set of individual-specific attributes, such as age, gender, and education; S_j is a vector of household-level characteristics, such as income; $\beta_0, \beta_1, \beta_A,$ and β_S are corresponding coefficients to be estimated; and the error includes a household-level component μ_j as well as an idiosyncratic error term ε_{ij}.

To eliminate household unobservables, a household fixed-effects procedure is used whereby

(4-1) $$\Delta^j h_{ij} = \beta_1 \Delta^j T_{ij}^k P_j^k + \beta_A \Delta^j A_{ij} + \Delta^j \varepsilon_{ij},$$

where Δ^j is the within-household difference operator.

Estimates of β_1 will not be consistent if the presence of a person around the stove during cooking time is related to his/her health endowments, i.e., $E(T_{ij}^k \varepsilon_{ij}) \neq 0$. For example, some may associate an efficiency gain with assigning less healthy women to the cooking task who are unable to perform other tasks. If so, the estimate of β_1 will be biased upward. If perceptions are that illness can be easily spread though food preparation so that more healthy women are assigned to the cooking task, then the estimate of β_1 will be biased downward.

To deal with the problem of endogeneity of the presence in the kitchen during cooking time, similar to the approach by Pitt, et al (2006), I use the person's relationship to the head of household as an instrument for T_{ij}^k. In India, household hierarchy still plays an important role in determining women's tasks. A daughter-in-law or the wife of the head is more likely to work in the kitchen. In addition, having a sister, a sister-in-law, or a mother-in-law may also influence a person's time spent in the kitchen. Thus, I use a set of dummy variables as well as their interactions that capture the household hierarchy as instruments to identify the effect of IAP exposure during cooking on health. These instruments affect T_{ij}^k, but do not affect individual health. Because I use a household fixed effect, the estimation is valid if the instrument is correlated with the household-level health unobservables.

Incidence of Respiratory Symptoms as the Health Outcome

I use self-reported respiratory symptoms and doctor-measured lung capacity as health outcomes in the empirical analyses of this chapter. I first report the analyses for respiratory symptoms.

A. Overview of the Data

All three survey teams asked about respiratory symptoms (e.g., coughing, wheezing, and phlegming) in their health questions. However, the exact questions and who answered the questions was somewhat different. In NCAER's survey, which covered all four states, an adult woman in each household was asked to answer the questions about the health of each family member over the last month, including very young children. The question about respiratory symptoms was “Did <NAME> have a cough the last month?” The Energy Research Institute (TERI), which surveyed Uttarakhand, West Bengal, and Madhya Pradesh, and Sri Ramachandran Medical College (SRMC), which surveyed Tamil Nadu, asked each individual more than 12 years old to answer questions and their questions were also different. TERI’s question was “Do you frequently get a cough?” SRMC’s question was “Have you had cough in the past?”

In terms of wheezing, TERI’s question was “Do you ever get wheezing or whistling sound in your breathing?” and SRMC’s question was “Do you suffer from wheezing?” In terms of phlegming, TERI’s question was “Do you frequently bring up phlegm/sputum from your chest?” and SRMC’s question was to choose “Sputum quantity: scanty or copious.” In addition, both TERI and SRMC asked follow-up questions on coughing, wheezing, and phlegming. However, they were too difficult to combine into a unified response. I used TERI’s and SRMC’s data as the primary source of incidence of respiratory symptoms and used NCAER’s data on coughing for those who are younger than 12 years old. Symptoms in the TERI and SRMC data are self-reported while in the NCAER data they are reported by one interviewee (usually the children’s mother) for each household.

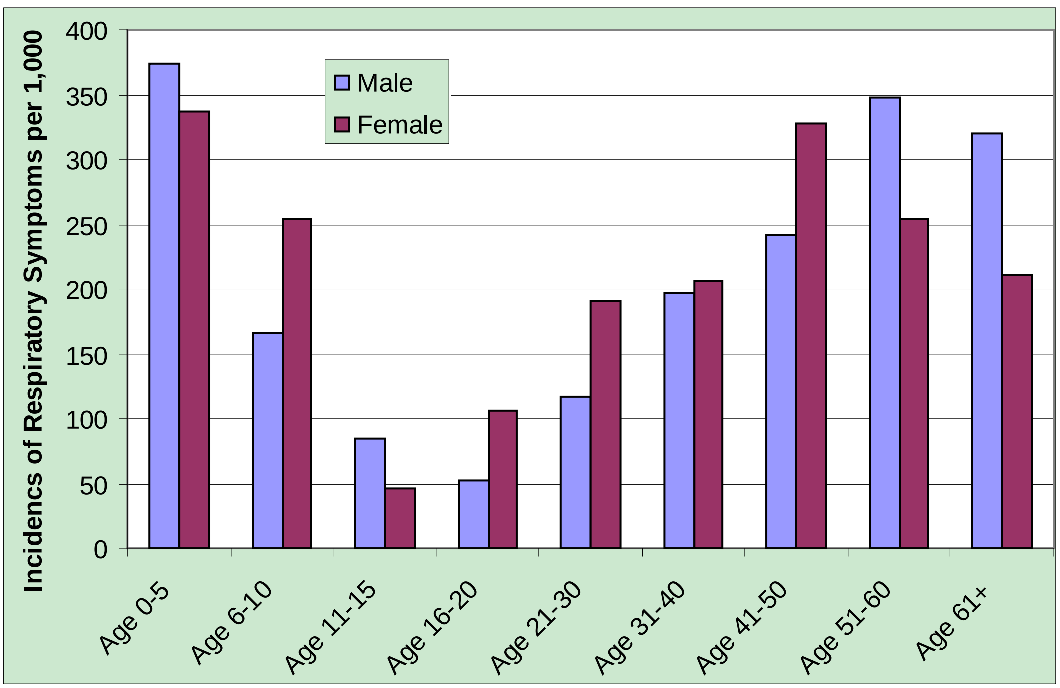
The reconciled data on incidence of respiratory symptoms is presented by state in Table 4-2 and by age group and gender in Figure 4-1. The figures and patterns are generally comparable with the incidence of respiratory symptoms reported in developing countries. For example, Pitt et al (2006) used the 2000-2003 Nutrition Survey of Bangladesh and reported that over 37% of boys and 32% of girls younger than five exhibited some respiratory symptoms. In addition, 5.4%

of all adults aged 16 and over and 22.1% of children of ages 2-9 reported respiratory symptoms in their sample. Table 4-3 provides summary statistics of variables used in this section.

Table 4-2. **Incidence of Respiratory Symptoms by State of Residence**

Symptom	Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu	Total
At Least One Symptom	18%	18%	27%	16%	21%
Coughing	15%	15%	26%	14%	18%
Wheezing	6%	6%	7%	8%	6%
Phlegming	5%	7%	6%	4%	6%
Number of Individuals	687	583	648	619	2537

Figure 4-1. **Incidences of Respiratory Symptoms for Males and Female by Age Group**



B. Estimates of the Effects of Typical Kitchen Presence

Typical kitchen presence is an indicator of whether the individual has high exposure to IAP. Since the health questionnaire for Tamil Nadu was surveyed by a different team than surveyed the other three states, I first determine whether the data for the four states are compatible. This is done by estimating a linear probability model separately for Tamil Nadu

Table 4-3. Summary Statistics of Variables

Variable	Mean	Standard. Deviation	Minimum	Maximum
Respiratory Symptoms (dummy)	0.192	0.394	0	1
Typical Kitchen Presence (dummy)	0.264	0.441	0	1
PM 2.5 Mean (mg/m^3)	0.570	0.398	0.058	2.669
PM 2.5 95th Percentile (mg/m^3)	2.529	2.423	0.090	15.057
Education (years)	4.861	4.562	0	15
Female (dummy)	0.479	0.500	0	1
Wife of Household Head (dummy)	0.174	0.379	0	1
Daughter-in-Law of Head (dummy)	0.038	0.191	0	1
Total Household Expenditure (100,000 rupees per year)	0.644	0.687	0	7.303
Smoking (dummy)	0.057	0.231	0	1
Age Categories				
Ages 0 to 5	0.134	0.341	0	1
Ages 6 to15	0.207	0.405	0	1
Ages 16 to 20	0.098	0.298	0	1
Ages 21 to 30	0.210	0.407	0	1
Ages 31 to 40	0.148	0.355	0	1
Ages 41 to 50	0.095	0.293	0	1
Ages 51 to 60	0.056	0.229	0	1
Ages 61and greater	0.052	0.222	0	1
State of Residence				
Uttarakhand	0.279	0.448	0	1
West Bengal	0.273	0.445	0	1
Madhya Pradesh	0.238	0.426	0	1
Tamil Nadu	0.210	0.408	0	1
Number of Individuals		2333		
Number of Households		522		

from the other three states. A Chow test of whether all states follow the same model aside from state dummies yields an F statistic of $F(13,2498) = 1.273$ corresponding to a *p*-value of 0.224, which cannot reject the hypothesis that the models are the same. Thus, I regard the data for all four states as compatible.

In addition, as symptoms for individuals older than 12 years old are self-reported and for individuals younger than 12 years old are non-self reported, there may be a systematic difference in reported results because individuals probably recall their own health better than others. Thus, another Chow test is employed to see whether the non-self reporting group is different than the self-reporting group. The Chow test that test for common coefficients versus different coefficients of all variables between the two groups yields an F statistic of $F(16,2492) = 1.425$ corresponding to a p-value of 0.1203, which cannot reject the hypothesis at common significance levels that the self-reporting and non-self reporting groups can be treated the same. Thus, I regard the data for the two groups as compatible.

Table 4-4 provides estimates of the effects of typical kitchen presence on the incidence of respiratory symptoms. The effects of age 61 or greater and residence in Tamil Nadu are represented in the constant term of this and subsequent regressions. Columns (1), (2), and (3) present estimates using a logit model, random-effects model, and fixed-effects model, respectively. Columns (4)-(7) present estimates considering the endogeneity of typical kitchen presence by using fixed-effects with instrumental variables (FE-IV) where instruments are derived by alternative methods. Instruments are derived by a linear probability model (LPM) in Column (4), by using a linear probability model with fixed effects (LPM-FE) in Column (5), by a logit model in Column (6), and by a logit model with fixed effects (Logit-FE) in Column (7). The estimation of instruments for typical kitchen presence is presented in Table 4-5, where ages

Table 4-4. **The Effects of Typical Kitchen Presence on the Incidence of Respiratory Symptoms**[a]

Estimator	(1) Logit	(2) RE	(3) FE	(4) FE-IV	(5) FE-IV	(6) FE-IV	(7) FE-IV	(8) Logit-FE-IV
Estimation of Instruments				LPM	LPM-FE	Logit	Logit-FE	Logit-FE
Typical Kitchen Presence	0.579**	0.086**	0.098**	0.143*	0.135*	0.142*	0.086*	0.697*
	[4.19]	[4.13]	[4.23]	[2.15]	[2.09]	[2.16]	[2.01]	[2.57]
Education	-0.047**	-0.007**	-0.007**	-0.006+	-0.007*	-0.006+	-0.007*	-0.054*
	[3.22]	[3.10]	[2.73]	[1.85]	[2.17]	[1.86]	[2.20]	[2.55]
Female	0.065	-0.001	-0.012	-0.028	-0.027	-0.028	-0.006	-0.012
	[0.53]	[0.04]	[0.64]	[0.86]	[0.84]	[0.86]	[0.22]	[0.07]
Household Expenditures	0.022	0.011						
	[0.25]	[0.60]						
Smoking	1.519**	0.262**	0.251**	0.257**	0.257**	0.258**	0.256**	1.522**
	[7.71]	[7.81]	[6.74]	[5.48]	[5.47]	[5.48]	[5.47]	[5.77]
Age Categories								
Ages 0 to 5	0.469*	0.090*	0.078+	0.069	0.068	0.069	0.084	0.409
	[1.96]	[2.27]	[1.76]	[1.24]	[1.23]	[1.25]	[1.52]	[1.25]
Ages 6 to 15	-0.480*	-0.084*	-0.097*	-0.102+	-0.103+	-0.102+	-0.099+	-0.807*
	[1.98]	[2.24]	[2.32]	[1.95]	[1.96]	[1.94]	[1.90]	[2.47]
Ages 16 to 20	-1.095**	-0.134**	-0.151**	-0.166**	-0.163**	-0.165**	-0.146*	-1.506**
	[3.36]	[3.12]	[3.13]	[2.67]	[2.64]	[2.66]	[2.42]	[3.45]
Ages 21 to 30	-0.610*	-0.102**	-0.123**	-0.138*	-0.133*	-0.137*	-0.124*	-1.008**
	[2.46]	[2.64]	[2.79]	[2.36]	[2.31]	[2.36]	[2.20]	[2.86]
Ages 31 to 40	-0.484+	-0.075+	-0.083+	-0.096+	-0.094	-0.096+	-0.082	-0.620+
	[1.94]	[1.92]	[1.89]	[1.66]	[1.63]	[1.66]	[1.47]	[1.77]
Ages 41 to 50	-0.031	-0.013	-0.035	-0.044	-0.047	-0.044	-0.032	-0.38
	[0.12]	[0.31]	[0.76]	[0.74]	[0.78]	[0.74]	[0.55]	[1.07]
Ages 51 to 60	0.164	0.002	-0.046	-0.048	-0.053	-0.048	-0.04	-0.409
	[0.58]	[0.03]	[0.92]	[0.76]	[0.84]	[0.75]	[0.64]	[1.14]
State of Residence								
Uttarakhand	-0.304*	-0.052+						
	[2.05]	[1.76]						
West Bengal	-0.704**	-0.105**						
	[4.32]	[3.50]						
Madhya Pradesh	0.106	0.017						
	[0.75]	[0.58]						
Constant	-0.998**	0.290**	0.275**	0.271**	0.276**	0.271**	0.280**	
	[4.06]	[6.97]	[7.07]	[5.57]	[5.68]	[5.57]	[5.75]	
Observations	2524	2524	2532	2532	2532	2532	2532	1440
Households		592	597	597	597	597	597	304
R^2 statistic			0.087	0.082	0.082	0.082	0.081	

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level. Variances of two stage estimators use the corrected mean squared error. Abbreviations are defined as follows: RE means random effects, FE means fixed effects, and LPM means linear probability model.

Table 4-5. First-Stage Estimates: The Determinants of Typical Kitchen Presence[a]

Regression Variable	(1) LPM	(2) LPM-FE	(3) Logit	(4) Logit FE
Education (years)	-0.006**	-0.0003	-0.049**	-0.004
	[3.28]	[0.13]	[3.50]	[0.16]
Female (dummy)	0.162**	0.171**	1.094**	1.632**
	[9.76]	[10.04]	[9.34]	[9.31]
Wife (dummy)	0.560**	0.568**	2.644**	3.260**
	[22.07]	[22.25]	[14.70]	[11.51]
Daughter-in-Law (dummy)	0.669**	0.770**	3.007**	4.093**
	[6.14]	[7.00]	[4.43]	[3.88]
Wife x Number of Daughters-in-Law	-0.250**	-0.248**	-1.278**	-1.525**
	[6.84]	[6.80]	[5.40]	[4.44]
Daughter-in-Law x Number of Daughters-in-Law	-0.136*	-0.127*	-0.607+	-0.596
	[2.32]	[2.13]	[1.79]	[1.26]
Wife x Daughter-in-Law	-0.056	-0.146+	-0.271	-1.013
	[0.71]	[1.84]	[0.54]	[1.21]
Age Categories				
Ages 0 to 5	0.122**	0.132**	0.833**	0.856*
	[3.44]	[3.55]	[3.12]	[2.30]
Ages 6 to 15	0.011	0.015	0.133	-0.131
	[0.33]	[0.44]	[0.50]	[0.36]
Ages 16 to 20	0.150**	0.142**	1.118**	1.133**
	[3.98]	[3.51]	[3.89]	[2.86]
Ages 21 to 30	0.069+	0.046	0.539+	0.262
	[1.93]	[1.17]	[1.90]	[0.65]
Ages 31 to 40	0.082*	0.077*	0.639*	0.466
	[2.27]	[2.01]	[2.24]	[1.19]
Ages 41 to 50	0.066+	0.095*	0.491+	0.431
	[1.73]	[2.37]	[1.67]	[1.05]
Ages 51 to 60	0.066	0.111**	0.489	0.824+
	[1.58]	[2.59]	[1.55]	[1.94]
Constant	0.075*	0.04	-2.393**	
	[2.38]	[1.21]	[9.47]	
Observations	3105	3097	3105	2735
Households		618		530
***R^2* statistic**	0.348	0.443		

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

61 and over are represented in the constant term. Column (8) presents estimates using a logit model with fixed effects and instrumental variables (Logit-FE-IV) where the instrumental variables are also based on a logit model with fixed effects. Note that in all models except the

logit models, the estimated coefficients of indicator variables (all variables other than household expenditures and education) can be interpreted as estimated probability effects.

In terms of model specifications, logit and probit models are generally preferred to the linear probability model (LPM) when the dependent variable in a regression model is a dummy variable because the latter is usually less efficient and predicted probabilities from the LPM can lie outside the 0-1 interval (Caudill, 1988, Donald and Rearden, 1990). However, with the Logit FE model, as shown in Table 4-4, households without variation in the incidence of respiratory symptoms are automatically dropped, which reduces the sample size by almost half and significantly limits the estimation precision. Because I am also interested in estimating the effect on these households and the linear models such as the RE and FE models based on LPM instrumentation produce estimates within the unit interval, I regard them as preferred. For the same reasons, the LPM-FE model is also preferred in the first stage specifications shown in Table 4-5. Therefore, the estimates in Column (5) of Table 4-4 are the preferred estimates in this analysis. Thus, I focus further discussion on these estimates.

As shown in Table 4-5, the instruments are dummy variables indicating whether the individual is a wife of the head or a daughter-in-law, the interaction of wife and daughter-in-law with the number of daughters-in-law, and the interaction of daughter-in-law with the presence of any wife of the head of the household. This set of hierarchical identifying variables follows the instruments used by Pitt et al (2006) to explain cooking time. The set of instrumental variables are jointly significant in column (2) of Table 4-5 with an F-statistic of $F(5,2465) = 108.82$ corresponding to a p-value less than 0.0001. In addition, a score test for overidentifying restrictions is conducted to verify the validity of the instruments. The score test has a chi-squared statistic of $\chi^2(4) =$ 4.4746 corresponding to a *p*-value of 0.3456, which means the hypothesis that the instruments are valid cannot be rejected.

The sign patterns of a person's position in the household hierarchy in column (2) of Table 4-5 generally conform to those indicated in the anthropological literature: being a wife or a daughter-in-law increases the chances of cooking; an increased number of daughters-in-law in a household decreases the wife's chances of cooking as does the presence of a daughter-in-law; and the presence of a wife in the household decreases the daughter-in-law's chance of cooking. The sign patterns of the age categories are also within expectations. Compared to the reference age category of 61 or more years of age, all other age categories have positive signs. Three age categories have particularly high coefficients: ages 16 to 20, which are more likely to represent daughter-in-laws; ages 0 to 5, which are likely to represent children with their mothers when their mothers are cooking; and ages 51 to 60 which are more likely to represent wives.

Turning to the second-stage estimates in Table 4-4, in addition to typical kitchen presence, other independent variables include education, gender, household annual expenditure, whether the individual smokes, age categories, and dummy variables for state of residence. Typical kitchen presence has positive and statistically significant effects on the incidence of respiratory symptoms in all model specifications although the magnitude varies. Smoking also has positive and statistically significant effects with magnitudes much larger than for typical kitchen presence, which is consistent with medical evidence.

Education has negative and statistically significant effects across all specifications, which is also expected. The effects of being a female and household expenditure are not statistically different from zero. In terms of age categories, compared to those who are 61 or older, individuals with an age from 6 to 30 have a lower chance of respiratory symptoms and the effect is statistically significant across specifications. The reason I use categorical age variables is because, as shown in Figure 4-1, the relationship between age and the incidence of respiratory symptoms is neither linear nor quadratic. Use of age classifications appears to capture age effects better than a simple function of age because the same factors do not affect each age group. For example, children ages 0 to 5 are those who are usually close to their mothers for care whereas children ages 6 to 15 are those who likely to go to school regularly.

The preferred specification in Column (5) of Table 4-4 shows that typical kitchen presence increases the probability of reporting a respiratory symptom by 13.5 percentage points, which is about one half of the effect of being a smoker. The estimated effect of typical kitchen presence in Column (5) correcting for endogeneity is higher than the one in Column (3), suggesting that women with better respiratory health are sorted into cooking responsibilities. In addition, one more year of schooling reduces the probability of reporting a respiratory system by 0.7 percentage points. Being in an age category of 16- 20 or 21-30 can reduce the probability of reporting a respiratory system by 16.3 percentage points and 13.3 percentage points, respectively. All these effects are statistically significant at either the 5% or 1% level.

C. Estimates of the Effects of Kitchen IAP Levels and Typical Kitchen Presence

One advantage of the analysis in this dissertation is that the effect of pollution intensity on the incidence of respiratory symptoms can be assessed using the measured IAP levels in the kitchen. I use the estimates from Chapter 3 of the typical IAP levels in the kitchen for this analysis. Both the PM 2.5 mean and PM 2.5 95th percentile are used to represent pollution intensities.

Table 4-6 provides estimates of the effects of typical kitchen presence and kitchen IAP levels measured by the PM 2.5 mean on the incidence of respiratory symptoms. As discussed above, linear models such as the RE and FE models based on LPM instrumentation are preferred to the logit model in this analysis. Thus, Table 4-6 does not report the results using the logit model but rather reports only the results using the RE, FE, and FE-IV models (where instruments are derived by the LPM-FE).

For each model, I use two types of specifications. One includes typical kitchen presence, the PM 2.5 mean in the kitchen, and an interaction term of the two separate variables and the other only includes the interaction term. Because typical kitchen presence and the interaction term of typical kitchen presence with the PM 2.5 mean are highly correlated (correlation 0.81), the magnitudes and significance levels of the interaction term decrease substantially when including both terms in the regression. For specifications (1), (3), and (5), testing the joint significance of typical kitchen presence and the interaction term, typical kitchen presence has a statistically significant positive effect across all models. The PM 2.5 mean in the kitchen, however, is not statistically significant for model FE-IV (Column (5)). This is within expectation. If a person is not typically in the kitchen, then he/she is not affected by IAP levels in kitchen. Because I am interested in the aggregated health effect of IAP exposure, i.e., the pollution intensity effect to those people who are exposed to IAP, Column (6) in Table 4-6, which includes only the interaction term, is the preferred model. It shows that every 1 mg/m^3 increase in the PM 2.5 mean in the kitchen is associated with an 11.9 percentage point increase in the probability of reporting a respiratory symptom for those who are typically in the kitchen. This effect is statistically significant at the 10% level with a *p*-value of 0.0540.

Table 4-6. The Effects of Kitchen IAP Levels (PM 2.5 Mean) and Typical Kitchen Presence on the Incidence of Respiratory Symptoms[a]

Regression Variable	(1)	(2)	(3)	(4)	(5)	(6)
	RE		FE		FE-IV	
Typical Kitchen Presence (TKP)	0.012		0.034		0.109+	
	[0.35]		[0.94]		[1.71]	
PM 2.5 Mean	0.002		0.146		0.476	
	[0.07]		[0.01]		[0.02]	
TKP x PM 2.5 Mean	0.143**	0.156**	0.118*	0.155**	0.051	0.119+
	[2.94]	[4.99]	[2.29]	[4.53]	[0.69]	[1.93]
Education (years)	-0.007**	-0.007**	-0.008**	-0.008**	-0.009**	-0.009**
	[3.06]	[3.11]	[3.05]	[3.09]	[3.11]	[3.32]
Female (dummy)	-0.003	-0.001	-0.012	-0.006	-0.029	-0.001
	[0.16]	[0.05]	[0.63]	[0.35]	[1.07]	[0.05]
HH Expenditures	0.007	0.007				
	[0.40]	[0.38]				
Smoking (dummy)	0.276**	0.276**	0.275**	0.274**	0.282**	0.274**
	[7.81]	[7.81]	[6.98]	[6.95]	[7.06]	[6.90]
Age Categories						
Ages 0 to 5	0.085*	0.086*	0.074	0.075+	0.061	0.068
	[2.11]	[2.12]	[1.64]	[1.66]	[1.34]	[1.50]
Ages 6 to 15	-0.081*	-0.082*	-0.091*	-0.092*	-0.098*	-0.098*
	[2.13]	[2.14]	[2.13]	[2.15]	[2.30]	[2.29]
Ages 16 to 20	-0.114**	-0.114**	-0.126*	-0.123*	-0.139**	-0.123*
	[2.61]	[2.61]	[2.56]	[2.52]	[2.74]	[2.46]
Ages 21 to 30	-0.092*	-0.091*	-0.105*	-0.101*	-0.115*	-0.093*
	[2.31]	[2.29]	[2.33]	[2.26]	[2.42]	[2.03]
Ages 31 to 40	-0.065	-0.064	-0.066	-0.063	-0.075	-0.053
	[1.61]	[1.59]	[1.47]	[1.40]	[1.58]	[1.16]
Ages 41 to 50	0.011	0.012	-0.018	-0.013	-0.031	-0.01
	[0.26]	[0.29]	[0.37]	[0.29]	[0.63]	[0.20]
Ages 51 to 60	0.026	0.027	-0.021	-0.019	-0.023	-0.009
	[0.56]	[0.57]	[0.41]	[0.38]	[0.45]	[0.18]
State of Residence						
Uttarakhand	-0.056+	-0.055+	-0.056+			
	[1.69]	[1.85]	[1.69]			
West Bengal	-0.084**	-0.083**	-0.084**			
	[2.68]	[2.74]	[2.68]			
Madhya Pradesh	0.03	0.03	0.03			
	[0.97]	[1.02]	[0.97]			
Constant	0.263**	0.264**	0.171	0.254**	-0.015	0.254**
	[5.92]	[6.17]	[0.01]	[6.41]	[0.00]	[6.39]
Observations	2333	2333	2333	2333	2333	2333
Households	522	522	522	522	522	522
R^2 statistic				0.092	0.085	0.084

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

To test whether IAP concentrations have different effects by age categories, the regression in Column (6) of Table 4-6 was expanded by adding interaction terms of the PM 2.5 mean with each age category dummy. The F-test for the joint exclusion of these interaction terms yields an F-statistic of F (6, 1793) = 0.25 with a corresponding *p*-value of 0.9593. Thus, adding the interaction terms adds virtually no explanation and the absence of age-specific effects of IAP cannot be rejected.

The estimates in Table 4-6 assume that the exposure-response relation is linear. However, this may not be a valid assumption. For example, Ezzati and Kammen (2001a) found that acute respiratory infections (ARI) and acute lower respiratory infections (ALRL) are increasing concave functions of average daily exposure to PM 10 pollution, with the rate of increase declining for exposures above 1-2 mg/m^3. To test linearity, I present further results in Table 4-7 where exposure is represented by exposure categories similar to Ezzati and Kammen (2001): (1) 0-0.2 mg/m^3 with a mean of 0.147 mg/m^3, (2) 0.2-0.5 mg/m^3 with a mean of 0.337 mg/m^3, (3) 0.5-1 mg/m^3 with a mean of 0.711 mg/m^3, (4) 1-2 mg/m^3 with a mean of 1.284 mg/m^3, and (5) more than 2 mg/m^3 with a mean of 2.312 mg/m^3.

The five exposure categories in Table 4-7 are jointly statistically significant at the 10% level with an F–statistic of F(4,1920) = 1.99 and a corresponding *p*-value of 0.0768 for the preferred model in Column (3). The exposure-response relationship associated with the mean values in the five exposure categories is illustrated in Figure 4-2. The results are not consistent with a concave relationship, but closer to a linear relationship when the exposure level is greater than 0.2 mg/m^3. As the exposure category for greater than 2 mg/m^3 has a very high coefficient for the incidence of respiratory symptoms, the results support the suggestion by Bruce et al (1998) that public-health programs directed at adverse impacts of IAP in developing countries should

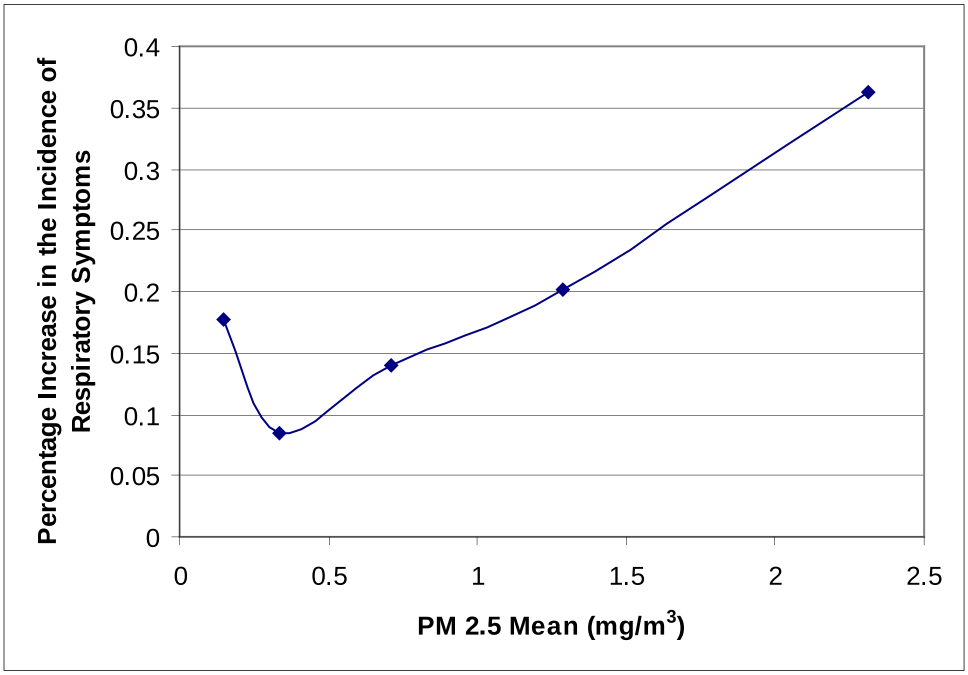
Table 4-7. The Effects of Exposure Categories in the Kitchen on the Incidence of Respiratory Symptoms[a]

Regression Variable	(1) RE	(2) FE	(3) FE-IV	Mean for (3)
TKP x PM 2.5 Mean <0.2 mg/m3	0.102*	0.123*	0.178*	4.51%
	[2.37]	[2.53]	[2.33]	
TKP x PM 2.5 Mean 0.2-0.5 mg/m3	0.005	0.035	0.085	9.52%
	[0.18]	[1.00]	[1.37]	
TKP x PM 2.5 Mean 0.5-1 mg/m3	0.103**	0.120**	0.140*	11.05%
	[3.53]	[3.63]	[2.28]	
TKP x PM 2.5 Mean 1-2 mg/m3	0.230**	0.244**	0.202+	2.27%
	[3.41]	[3.24]	[1.77]	
TKP x PM 2.5 Mean >2 mg/m3	0.341+	0.359+	0.363	0.31%
	[1.80]	[1.78]	[1.34]	
Education (years)	-0.007**	-0.007**	-0.007**	4.94
	[2.94]	[2.69]	[2.72]	
Female (dummy)	0.006	-0.011	-0.024	48.1%
	[0.33]	[0.59]	[0.97]	
HH Expenditures	0.01			
	[0.55]			
Smoking (dummy)	0.258**	0.245**	0.250**	6.20%
	[7.72]	[6.63]	[6.68]	
Age Categories				
Ages 0 to 5	0.093*	0.081+	0.068	13.19%
	[2.34]	[1.83]	[1.53]	
Ages 6 to 15	-0.085*	-0.094*	-0.104*	20.10%
	[2.26]	[2.25]	[2.46]	
Ages 16 to 20	-0.131**	-0.147**	-0.162**	9.68%
	[3.05]	[3.04]	[3.27]	
Ages 21 to 30	-0.098*	-0.118**	-0.128**	21.37%
	[2.54]	[2.70]	[2.79]	
Ages 31 to 40	-0.079*	-0.087*	-0.094*	15.44%
	[2.01]	[1.99]	[2.04]	
Ages 41 to 50	-0.012	-0.034	-0.046	9.52%
	[0.30]	[0.74]	[0.95]	
Ages 51 to 60	-0.006	-0.052	-0.053	5.49%
	[0.13]	[1.03]	[1.05]	
State of Residence				
Uttarakhand	-0.057+			
	[1.94]			
West Bengal	-0.109**			
	[3.59]			
Madhya Pradesh	0.015			
	[0.52]			
Constant	0.294**	0.276**	0.278**	
	[7.08]	[7.09]	[7.11]	
Observations	2524	2532	2532	
Households	592	597	597	
R^2 statistic		0.092	0.083	

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

concentrate on reducing average exposure to levels below 2 mg/m^3. However, the results here also suggest that further significant gains would be forthcoming from reducing exposure levels below 1 mg/m^3.

Figure 4-2. Percentage Increase in Incidence of Respiratory Symptoms by Exposure



Parallel to Table 4-6, Table 4-8 presents the results using the PM 2.5 95th percentile as the IAP concentration indicator. The preferred specification in Column (6) shows that a 1 mg/m^3 increase in the PM 2.5 95th percentile in the kitchen is associated with a 0.02 percentage point increase in the probability of reporting a respiratory symptom for those who are typically in the kitchen. This effect is statistically significant at the 5% level with a *p*-value of 0.040. This effect is only 1/5 of the effect when using the PM 2.5 mean as the indicator. Since the PM 2.5 95th percentile represents a short-period of high pollution intensity while the PM 2.5 mean represents the 24-hour average pollution intensity, this result suggests that the daily average pollution intensity has more impact on respiratory health.

Table 4-8. The Effects of Kitchen IAP Levels (PM 2.5 95th Percentile) and Typical Kitchen Presence on the Incidence of Respiratory Symptoms[a]

Regression Variable	(1)	(2)	(3)	(4)	(5)	(6)
	RE		FE		FE-IV	
Typical Kitchen Presence (TKP)	0.033		0.049		0.090**	
	[1.18]		[1.59]		[3.69]	
PM 2.5 95th Percentile (PM 95th)	0.003		0.029		-0.002	
	[0.56]		[0.01]		[0.00]	
TKP x PM 95th	0.024**	0.030**	0.021*	0.029**	0.015	0.023*
	[3.00]	[5.04]	[2.47]	[4.44]	[1.31]	[2.05]
Education (years)	-0.007**	-0.007**	-0.008**	-0.009**	-0.008**	-0.009**
	[2.95]	[3.09]	[3.04]	[3.14]	[3.00]	[3.35]
Female (dummy)	-0.002	0.005	-0.012	0	-0.024	0.003
	[0.13]	[0.29]	[0.61]	[0.01]	[1.12]	[0.16]
HH Expenditures	0.008	0.007				
	[0.46]	[0.39]				
Smoking (dummy)	0.275**	0.274**	0.274**	0.271**	0.278**	0.272**
	[7.78]	[7.75]	[6.96]	[6.89]	[7.03]	[6.87]
Age Categories						
Ages 0 to 5	0.085*	0.086*	0.075+	0.076+	[1.53]	0.07
	[2.10]	[2.13]	[1.66]	[1.69]	-0.092*	[1.54]
Ages 6 to 15	-0.081*	-0.083*	-0.091*	-0.092*	[2.15]	-0.097*
	[2.13]	[2.17]	[2.13]	[2.17]	-0.133**	[2.28]
Ages 16 to 20	-0.115**	-0.113*	-0.126*	-0.120*	[2.68]	-0.120*
	[2.63]	[2.57]	[2.56]	[2.46]	-0.111*	[2.42]
Ages 21 to 30	-0.093*	-0.088*	-0.104*	-0.096*	[2.44]	-0.089*
	[2.34]	[2.22]	[2.32]	[2.14]	-0.071	[1.97]
Ages 31 to 40	-0.064	-0.059	-0.065	-0.057	[1.56]	-0.049
	[1.59]	[1.48]	[1.44]	[1.27]	-0.025	[1.08]
Ages 41 to 50	0.012	0.017	-0.016	-0.008	[0.53]	-0.006
	[0.28]	[0.39]	[0.35]	[0.17]	-0.023	[0.12]
Ages 51 to 60	0.024	0.027	-0.021	-0.017	[0.44]	-0.007
	[0.52]	[0.58]	[0.42]	[0.33]		[0.13]
State of Residence						
Uttarakhand	-0.065+	-0.057+				
	[1.95]	[1.92]				
West Bengal	-0.089**	-0.080**				
	[2.83]	[2.68]				
Madhya Pradesh	0.029	0.033				
	[0.95]	[1.11]				
Constant	0.259**	0.262**	0.179	0.252**	0.258	0.253**
	[5.97]	[6.14]	[0.01]	[6.38]	[0.02]	[6.36]
Observations	2333	2333	2333	2333	2333	2333
Households	522	522	522	522	522	522
***R^2* statistic**			0.093	0.092	0.091	0.084

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

Spirometry Indicators as the Health Outcome

Although self-reported symptoms are common in the survey data, an important limitation of using these responses is vulnerability to systematic errors in the health variables depending on whether people perceive themselves as ill. These perceptions are likely to vary systematically according to education, access to information, occupation, how the question is phrased, how the interviewers asked the question, and other factors. The following analysis using doctor-measured spriometry indicators as the health outcome is considered in the remainder of this chapter as a way of avoiding this problem.

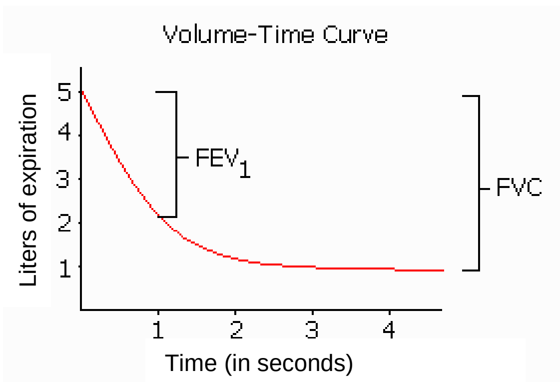
Lung function is directly related to respiratory health. Respiratory diseases can be classified as either obstructive (i.e., conditions that impede the rate of flow into and out of the lungs such as asthma) or restrictive (i.e., conditions that cause a reduction in the functional volume of the lungs such as pulmonary fibrosis) (Martin, 1984 and OAMIG, 2008). Spirometry is the most basic and frequently performed test of lung function. Spirometry is used to measure the rate of airflow during maximal expiratory effort after maximal inhalation. Several measurements are typically used in spriometry as illustrated in Figure 4-3 (Babaie, 1998):

- FVC (Forced Vital Capacity) — This is the total volume of air expired after a full inhalation. Patients with obstructive lung disease usually have a normal or only slightly decreased vital capacity. Patients with restrictive lung disease have a decreased vital capacity.
- FEV1 (Forced Expiratory Volume in 1 Second) — This is the volume of air expired in the first second during maximal expiratory effort. This measure is reduced in both obstructive and restrictive lung disease. It is reduced by obstructive lung disease

because of increased airway resistance. It is reduced in restrictive lung disease because of the low vital capacity.

- FEV1/FVC — This is the percentage of the vital capacity which is expired in the first second of maximal expiration. In healthy patients, the FEV1/FVC is usually around 70%. In patients with obstructive lung disease FEV1/FVC decreases and can be as low as 20-30% in severe obstructive airway disease. Restrictive disorders have a near normal FEV1/FVC.

Figure 4-3. **Spirometry: The Volume-Time Curve**



Source: Babaie (1998).

As indications of respiratory health, spriometry measurements are also related to a person's gender, age, height, and ethic group. Males have higher lung capacity than females. Children's lung capacity increases as they grow, but after age 20 lung capacity usually decreases (Berne and Levy, 1998). Lung capacity is generally larger for taller people. Genetics also plays a role. For example, Tibetan people, who live high on the mountains, have larger lung capacities.

A. Overview of the Data

As part of the HEED survey, a spirometry test was performed in the field with a portable spirometer on three to seven individuals per household with ages of 15 years and older. Spriometric measurements included FVC, FEV1, and the ratio between the two, FEV1/FVC. All spirometry measurements were recorded in adherence with the joint American Thoracic Society (ATS) and European Respiratory Society guidelines (Naymoff, 2007). This analysis uses the best of the three readings. Height was also measured by the field team according to standard protocol when spirometry was performed. Table 4-9 provides summary statistics of key variables used in this section. For comparison, normal adult lung capacity is 3 to 5 liters (Berne and Levy, 1998). The study from Udwadia et al (1987) analyzing lung function of 760 non-smoking healthy Indian subjects from 15 to 65 years of age found that their spirometric values (FVC, FEV1) were lower than those reported from the West. In their study, the mean FVC for males and females is 3.5 liters and 2.48 liters, respectively. In the HEED data, the mean FVC is slightly lower than the mean value in Udwadia et al (1987), with a value of 3.2 liters for males and 2.36 liters for females.

Table 4-9. Summary Statistics of Spirometry Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
FEV1 (liters)	2.315	0.673	0.530	4.380
FVC (liters)	2.750	0.752	0.880	5.550
FEV1/FVC	0.841	0.089	0.288	1.000
Education (years)	5.838	4.737	0	15
Female (dummy)	0.536	0.499	0	1
Smoking (dummy)	0.140	0.348	0	1
Age (years)	37.063	13.231	15	80
Height (cm)	156.652	8.953	130	182
Number of individuals	776			

B. Estimates of the Effects of Kitchen IAP Levels and Typical Kitchen Presence

To measure the respiratory health outcome, I use the three indicators available in the data: FEV1, FVC, and FEV1/FVC. I first detail the estimation results for FEV1 and then present and compare the estimates for the other two.

Table 4-10 provides estimates of the effects of the PM 2.5 mean in the kitchen and typical kitchen presence on FEV1. In addition to the IAP exposure variable(s), the control variables include education, gender, household expenditures, whether the person smokes, age, height, and state of residence dummies. I use a quadratic form for age because lung capacity usually decreases after age 20 (Berne and Levy, 1998) and a quadratic form appears to have a better goodness of fit (e.g. higher R^2 statistic) than using age categories.[4] Different approaches to estimation, including OLS, RE, FE, and FE-IV, are used. The first stage for the FE-IV model is the same as in Table 4-5. As the effects of height and age on lung function may be different for females than for males (Udwadia, et al, 1987), a Chow test is conducted to evaluate whether males and females have different coefficients for each factor. The Chow test yields an F-statistic of $F(6,323) = 1.48$ with a corresponding *p*-value of 0.1842. Thus, the hypothesis of common effects of these variables on males and females cannot be rejected.

As shown in Table 4-10, female gender has a statistically significant negative effect and height has a statistically significant positive effect on FEV1 across all specifications as expected. With OLS (Columns (1) and (2)) and RE (Columns (3) and (4)) estimation, residence in Uttarakhand has a statistically significant positive effect on FEV1 compared to the reference state, Tamil Nadu. This fits expectations because Uttarakhand is in northern India at a higher altitude than Tamil Nadu.

With FE (Columns (5) and (6)) and FE-IV (Columns (7) and (8)) estimation, the interaction term between typical kitchen presence and the PM 2.5 mean becomes statistically significant, showing a negative effect on FEV1. Education is statistically insignificant, which seems reasonable. With FE-IV estimation, smoking has a statistically significant negative effect

[4] For example, for the specification of Column (5) in Table 4-10, the R^2 statistic shows slight improvement from 0.661 to 0.663 when using a quadratic form of the age variable instead of using age categories.

Table 4-10. The Effects of Kitchen IAP Levels Measured as PM 2.5 Mean and Typical Kitchen Presence on FEV1[a]

Regression Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS		RE		FE		FE-IV	
Typical Kitchen Presence (TKP)	0.036		0.046		0.063		-0.04	
	[0.62]		[0.82]		[0.74]		[0.65]	
TKP x PM 2.5 Mean	-0.077	-0.048	-0.098	-0.06	-0.221*	-0.164*	-0.273*	-0.284*
	[1.10]	[0.92]	[1.39]	[1.13]	[1.98]	[2.05]	[1.99]	[2.08]
Education (years)	0.008*	0.009*	0.007+	0.008+	0.002	0.002	0.001	0.001
	[2.09]	[2.20]	[1.72]	[1.84]	[0.22]	[0.21]	[0.13]	[0.17]
Female (dummy)	-0.337**	-0.323**	-0.321**	-0.302**	-0.239**	-0.218**	-0.170*	-0.193**
	[6.38]	[6.78]	[6.17]	[6.46]	[3.36]	[3.35]	[2.16]	[2.74]
HH Expenditures	-0.043	-0.045	-0.042	-0.044				
	[1.11]	[1.16]	[0.99]	[1.03]				
Smoking (dummy)	-0.068	-0.067	-0.073	-0.073	-0.116	-0.118	-0.126+	-0.123+
	[1.30]	[1.29]	[1.43]	[1.42]	[1.61]	[1.63]	[1.73]	[1.70]
Age (years)	-0.015*	-0.015*	-0.014*	-0.014*	-0.004	-0.003	-0.001	-0.002
	[2.39]	[2.34]	[2.29]	[2.21]	[0.44]	[0.36]	[0.12]	[0.21]
Age Squared	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002*	-0.0002*	-0.0002*	-0.0002*
	[0.86]	[0.93]	[1.07]	[1.17]	[2.23]	[2.31]	[2.52]	[2.46]
Height	0.033**	0.033**	0.035**	0.035**	0.042**	0.042**	0.042**	0.042**
	[13.79]	[13.79]	[14.51]	[14.50]	[12.23]	[12.22]	[12.17]	[12.18]
State of Residence								
Uttarakhand	0.179**	0.177**	0.171**	0.169**				
	[3.55]	[3.53]	[3.11]	[3.08]				
West Bengal	0.037	0.04	0.036	0.039				
	[0.75]	[0.81]	[0.67]	[0.74]				
Madhya Pradesh	-0.057	-0.056	-0.056	-0.056				
	[1.25]	[1.25]	[1.13]	[1.12]				
Constant	-2.085**	-2.091**	-2.359**	-2.365**	-3.608**	-3.610**	-3.596**	-3.583**
	[5.06]	[5.07]	[5.75]	[5.77]	[6.18]	[6.18]	[6.16]	[6.14]
Observations	776	776	776	776	776	776	776	776
***R^2* statistic**	0.578	0.578			0.664	0.663	0.664	0.664
Households			440	440	440	440	440	440

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

on FEV1 at the 10% level, which is consistent with the medical evidence that smoking is the most common cause of chronic obstructive pulmonary disease (COPD) and the medical fact that FEV1 is reduced by obstructive lung disease (Lapperre, et al, 2007).

Typical kitchen presence and the interaction term of typical kitchen presence with the PM 2.5 mean in the kitchen is jointly significant at the 10% level in Column (7) with an F-statistic of $F(2, 328) = 2.37$ and a corresponding *p*-value of 0.0946. For the same reasons discussed earlier, Column (8) is the preferred specification. It shows that a 1 mg/m^3 increase in the PM 2.5 mean can reduce the FEV1 of a person who is typically in the kitchen by 0.284 liter. This effect is statistically significant at 5% level with a *p*-value of 0.038 and more than double the effect of smoking.

For comparison, Table 4-11 presents the FE-IV estimates for all spriometry measures: FEV1, FVC, and FEV1/FVC. The PM 2.5 mean and 95^{th} percentile that represent different pollution intensities are used separately for each model. Columns (2), (4), (6), (8), (10), and (12) are preferred specifications because they give the direct effects of IAP exposure intensity on health. The interaction term between typical kitchen presence and the PM 2.5 mean has a statistically significant negative effect on both FEV1 (at the 5% level with a *p*-value of 0.038) and FVC (at the 10% level with a *p*-value of 0.084) and their magnitudes are similar. The interaction term between typical kitchen presence and the PM 2.5 95^{th} percentile has a statistically significant negative effect on FEV1 at the 10% level with a *p*-value of 0.087. This term also has a negative effect on FVC, but it is not statistically significant.

Again, the magnitude of the coefficients using the PM 2.5 95^{th} percentile are much smaller than the ones using the PM 2.5 mean, generally around 13-14% of the latter. Again, this shows that the daily average pollution intensity has a greater impact on respiratory health than

Table 4-11. FE-IV Estimates: The Effects of IAP Exposure on the Spirometry Measures[a]

Regression Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	FEV1				FVC				FEV1/FVC			
TKP	-0.04		-0.046		-0.08		-0.086		0.014		0.014	
	[0.65]		[0.75]		[1.23]		[1.32]		[1.34]		[1.31]	
TKP x PM 2.5 mean	-0.273*	-0.284*			-0.233	-0.254+			-0.027	-0.024		
	[1.99]	[2.08]			[1.57]	[1.73]			[1.16]	[1.01]		
TKP x PM 2.5 95th Percentile			-0.038	-0.039+			-0.03	-0.033			-0.005	-0.004
			[1.65]	[1.72]			[1.22]	[1.33]			[1.23]	[1.13]
Education (years)	0.001	0.001	0.001	0.002	0.0003	0.001	0.001	0.001	0.0001	-0.00002	0.0001	-0.00002
	[0.13]	[0.17]	[0.17]	[0.21]	[0.04]	[0.11]	[0.08]	[0.15]	[0.06]	[0.02]	[0.05]	[0.02]
Female (dummy)	-0.170*	-0.193**	-0.195*	-0.223**	-0.240**	-0.286**	-0.264**	-0.317**	0.003	0.011	0.002	0.01
	[2.16]	[2.74]	[2.59]	[3.39]	[2.84]	[3.78]	[3.26]	[4.47]	[0.23]	[0.92]	[0.13]	[0.88]
Smoking (dummy)	-0.126+	-0.123+	-0.117	-0.114	-0.099	-0.094	-0.091	-0.085	-0.016	-0.017	-0.016	-0.017
	[1.73]	[1.70]	[1.61]	[1.57]	[1.27]	[1.20]	[1.17]	[1.09]	[1.31]	[1.39]	[1.25]	[1.34]
Age (years)	-0.001	-0.002	-0.003	-0.004	0.009	0.008	0.008	0.006	-0.002	-0.002	-0.002	-0.002
	[0.12]	[0.21]	[0.31]	[0.42]	[1.01]	[0.85]	[0.86]	[0.68]	[1.48]	[1.31]	[1.57]	[1.39]
Age Squared	-0.0002*	-0.0002*	-0.0002*	-0.0002*	-0.0003**	-0.0003**	-0.0003**	-0.0003**	-0.00001	-0.00001	-0.00001	-0.00001
	[2.52]	[2.46]	[2.35]	[2.26]	[3.00]	[2.86]	[2.86]	[2.70]	[0.68]	[0.86]	[0.61]	[0.81]
Height (cm)	0.042**	0.042**	0.042**	0.042**	0.051**	0.051**	0.051**	0.051**	-0.001	-0.001	-0.001	-0.001
	[12.17]	[12.18]	[12.15]	[12.15]	[13.77]	[13.74]	[13.74]	[13.71]	[1.26]	[1.24]	[1.25]	[1.24]
Constant	-3.596**	-3.583**	-3.583**	-3.567**	-4.785**	-4.758**	-4.773**	-4.743**	1.054**	1.049**	1.055**	1.050**
	[6.16]	[6.14]	[6.12]	[6.10]	[7.62]	[7.58]	[7.60]	[7.54]	[10.56]	[10.51]	[10.58]	[10.52]
Observations	776	776	776	776	776	776	776	776	776	776	776	776
Households	440	440	440	440	440	440	440	440	440	440	440	440
R^2 statistic	0.664	0.664	0.663	0.662	0.705	0.704	0.704	0.703	0.291	0.287	0.291	0.288

[a] The absolute values of t statistics are indicated in brackets. Significance is indicated by '+' at the 10% level; '*' at the 5% level; and '**' at the 1% level.

short-period high pollution intensity. Surprisingly, smoking does not have a significant impact on FVC. Since patients with obstructive lung disease usually have a normal or only slightly decreased FVC and patients with restrictive lung disease usually have a highly decreased FVC, this result suggests that smoking has more impacts on obstructive lung disease than on restrictive lung disease.

Columns (9)-(12) of Table 4-11 show that IAP exposure indicators do not have any statistically significant impacts on FEV1/FVC. Because restrictive lung disease causes decreases in both FVC and FEV1, the FEV1/FVC ratio can remain near normal (Babaie, 1998). The results in Table 4-11 thus imply that the major IAP effect is on restrictive lung disease. The main symptoms are shortness of breath and cough. Notable restrictive lung diseases include fibrosis, sarcoidosis, pleural effusion, hypersensitivity pneumonitis, asbestosis, pleurisy, lung cancer, infant respiratory distress syndrome (IRDS), acute respiratory distress syndrome (ARDS), and neurologic diseases affecting the ability of the body to alter respiration rate (including spinal cord injury), and mechanical diseases affecting pulmonary musculature (including myasthenia gravis, and severe acute respiratory syndrome) (OAMIG, 2008). The results here thus provide an explanation of why the literature includes more evidence of IAP impacts on certain respiratory diseases such as ALRI for children but less or inconsistent evidence of IAP impacts on other respiratory diseases such as asthma (a typical obstructive lung disease).

Furthermore, as shown in Table 4-11, the goodness of fit for regressions on FEV1 and FVC is very high, with R^2 statistics ranging from 0.66 to 0.71. Comparing to the R^2 statistics around 0.09 for regressions of the incidence of respiratory symptoms, this result shows that spirometry measurement is much more accurate in characterizing the effects of IAP while self-reported symptoms include much more noise in measurement.

Conclusions

In this chapter, I have analyzed and quantified the health impacts from IAP exposure. Both subjective self-reported respiratory symptoms and objective doctor-measured spirometric indicators (FEV1, FVC, and FEV1/FVC) are used to measure the health impacts. Similar to Pitt, et al (2006), I use household fixed-effects to eliminate household unobservables and use instruments related to a person's position in the household hierarchy to control for endogeneity of typical kitchen presence. The analysis shows the following important findings.

Typical kitchen presence causes a 13.5 percentage point increase in the probability of reporting a respiratory symptom. Comparing the results using the FE model and the FE-IV estimation approaches suggests that women with better respiratory health are sorted into cooking.

In terms of the effect of pollution intensity, an increase of 1 mg/m^3 in the PM 2.5 mean in the kitchen is associated with an 11.9 percentage point increase in the probability of reporting a respiratory symptom for those who are typically in the kitchen. An increase of 1 mg/m^3 in the PM 2.5 95^{th} percentile in the kitchen is associated with a 2.3 percentage point increase in the probability of reporting a respiratory symptom for those who are typically in the kitchen, which is only 1/5 of the effect using the PM 2.5 mean as the indicator. The comparison of these two results implies that average exposure rather than maximum instantaneous exposure offers a better explanation of the health effects.

An increase of 1 mg/m^3 in the PM 2.5 mean can reduce FEV1 of a person who is typically in the kitchen by 0.284 liters and reduce FVC by 0.254 liters. This effect is more than double of the effect of smoking and underscores the importance of considering the health impacts of IAP.

The effects of using the PM 2.5 95th percentile as the IAP intensity indicator on FEV1 and FVC are much smaller than when using the PM 2.5 mean, amounting to only 13-14% of the latter**.** This pattern is similar to the case where respiratory symptoms are used as the measure of health effects. Since the PM 2.5 95th percentile represents a short-period of high pollution intensity while the PM 2.5 mean represents the 24-hour average pollution intensity, this result also implies that daily average pollution intensity better explains the impact on respiratory health.

The IAP exposure indicators do not show any statistically significant impacts on FEV1/FVC. Because restrictive lung disease decreases both FVC and FEV1, with near normal FEV1/FVC, these results imply that IAP has major impacts on restrictive lung disease rather than obstructive lung disease.

Finally, the R^2 statistics for regressions on spirometric indicators are much higher than the ones on the respiratory symptoms. This result shows that spirometry measurement is much more accurate in characterizing the effects of IAP. In contrast, self-reported symptoms are apparently much more susceptible to noise in measurement, which explains why studies in developing countries have reported wide-ranging odds ratios (Smith, et al, 2000).

Chapter 5. Household Behavior with Respect to Energy Technology Choices

Introduction

Why do people use household energy technologies that can make them sick or even cause death? What are the factors that affect household preferences for cooking energy technologies? In this chapter, I use the results from previous chapters to examine these questions.

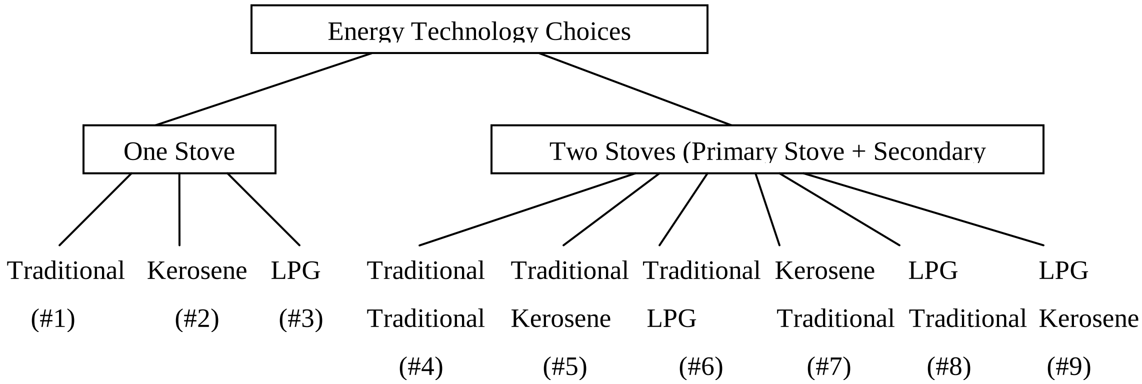
I apply a discrete choice model to estimate household behavior with respect to energy technology choices. I assume that each energy technology choice has certain attributes. How households value these attributes depends on their own characteristics. I assume a household selects an energy technology choice that maximizes its utility. The aim of the estimation is to quantify the factors that affect households' energy technology choices and to provide the basis for further welfare estimation of alternative policy interventions.

Energy Technology Choices

Energy technology choices focus on stove types. However, the choice options considered in this chapter are slightly different than the ones in Chapter 3. Because very few households use improved stoves, and costs of improved stoves vary significantly among households and are not available in the survey, I do not consider this stove option in the estimation.[5] In addition, although both LPG and kerosene stoves are clean stoves, they have quite different fixed and operating costs, so I treat them as separate energy technology choices. Thus, I reclassify the energy technology choices as shown in Figure 5-1 with nine final choices.

[5] Many households did not pay market prices for improved stoves because improved stoves were highly subsidized in India and subsidy levels varied significantly. The role of improved stoves is discussed further in Chapter 6.

Figure 5-1. Energy Technology Choices



Attributes of Energy Technology Choices

Households choose a cooking energy technology to fulfill their cooking needs. While all types of cooking energy technologies have cooking functions, they differ by attributes such as cost, convenience, and cleanliness. For example, LPG stoves are more expensive but more convenient and cleaner than traditional stoves. These attributes can be considered as technical coefficients that do not vary with households but only by energy technology choice. However, attributes in this form cannot be observed directly. For example, the observed cooking time, and IAP levels are determined by a combination of energy technology attributes and household characteristics for each chosen alternative. In order to estimate technical coefficients that are independent of household attributes, OLS regression analysis is used when it is possible to estimate these attributes as a function of both the energy technology choice and household characteristics. This enables separating out the effects of household characteristics for each energy technology choice. The statistical analysis in this chapter focuses on the role of three attributes in the energy technology choice: convenience, cleanliness, and cooking cost. Detailed estimation procedures are described as follows.

A. Convenience

I use cooking time to measure stove convenience. I use OLS regression to separate the effects of household characteristics from energy technology choices. In addition to state dummies, I consider household size as the main household characteristic affecting cooking time and assume that it affects cooking time with a quadratic relationship. Household size is expected to have a positive effect on cooking time, but the marginal effect is expected to decrease as household size increases due to economies of scale. The OLS regression results are shown in Table 5-1.

Table 5-1. Cooking Time Determination by Stove Type

Regression Variable	Coefficient	Standard Error	*t*-statistic	*p*-value
Energy Technology				
1—One Traditional Stove	0.856	0.257	3.330	0.001
2—One Kerosene Stove	0.272	0.346	0.780	0.433
3—One LPG Stove	-0.179	0.305	-0.590	0.557
4—Both Primary and Secondary Stoves are Traditional	0.453	0.307	1.480	0.140
5—Primary Stove is Traditional; Secondary Stove is Kerosene	0.451	0.285	1.580	0.114
6—Primary Stove is Traditional; Secondary Stove is LPG	0.875	0.283	3.100	0.002
7—Primary Stove is Kerosene; Secondary Stove is Traditional	0.079	0.357	0.220	0.825
8—Primary Stove is LPG; Secondary Stove is Traditional	-0.039	0.296	-0.130	0.894
Household Size	0.456	0.086	5.320	0.000
Household Size Squared	-0.025	0.006	-3.920	0.000
State of Residence				
Uttarakhand	2.350	0.151	15.580	0.000
West Bengal	1.496	0.149	10.060	0.000
Madhya Pradesh	0.561	0.147	3.800	0.000
Constant	0.261	0.362	0.720	0.471
Observations	561			
R^2 **statistic**	0.478			

All signs of coefficients are within expectations except for stove choice 8. Compared to the reference stove type 9, stove type 8 would normally be expected to have longer cooking time. However, the estimated coefficient is small and not statistically significant.

The average cooking time of the reference stove type is 2.64 hours. Adding the energy technology coefficients from Table 5-1, the estimated cooking times of various stove types are presented in Table 5-2. These numbers are generally consistent with the survey data reported by the Energy Sector Management Assistant Program (2004) where, on average, women spent 2.8 hours on cooking (including fuel collection) when using LPG stoves, 3.2 hours when using kerosene stoves, and 3.5 hours when using traditional stoves.

Table 5-2. Convenience (Cooking Time) by Energy Technology

Choice	Energy Technology	Cooking Time (Hours)
1	One Traditional Stove	3.49
2	One Kerosene Stove	2.91
3	One LPG Stove	2.46
4	Both Primary and Secondary Stoves are Traditional	3.09
5	Primary Stove is Traditional; Secondary Stove is Kerosene	3.09
6	Primary Stove is Traditional; Secondary Stove is LPG	3.51
7	Primary Stove is Kerosene; Secondary Stove is Traditional	2.72
8	Primary Stove is LPG; Secondary Stove is Traditional	2.60
9	Primary Stove is LPG; Secondary Stove is Kerosene	2.64

Source: Cooking time is estimated by adding the coefficient for each energy technology choice in Table 5.1 to the average cooking time of the reference stove type.

B. Cleanliness

I use IAP mean concentrations in the kitchen to measure stove cleanliness. Again, I use OLS regression to separate the effects of household characteristics from energy technology choices. The Chapter 3 OLS regression of IAP determinants included household characteristics and stove types although the stove types were defined slightly different than the current categorization. The estimated coefficients were then used to predict typical IAP exposures in households. Here I repeat the procedure using the natural log of the predicted IAP mean concentrations in the kitchen as the dependent variable but with the stove classification illustrated in Figure 5-1 and household characteristics defined in Chapter 3.

The results are shown in Table 5-3. As expected, the coefficients are highly significant and the R^2 statistic is greater than 0.995. Since the dependent variable is in the natural log form of IAP mean concentrations, the estimated IAP concentrations of stove type i (i = 1, 2, …,8) can be calculated as $Y_i = e^{\beta} Y_9$, where Y_9= 0.19 mg/m^3 where the average IAP mean concentration of the reference stove type (choice 9) and β are the corresponding coefficients in Table 5-3. The resulting calculations are presented in Table 5-4. As expected, using only clean stoves (LPG or kerosene or both) yields the lowest IAP concentrations. Also, LPG and kerosene stoves do not differ significantly in terms of pollution. By switching from using one traditional stove to an LPG stove or a kerosene stove, an average household can reduce IAP mean concentrations by more than 60%, or 0.35 mg/m^3.

C. Cooking Cost

Cooking cost includes two types of cost: stove cost and fuel cost. Stove cost can be considered as a fixed capital cost and fuel cost can be considered as operating cost. The monthly cooking cost is the sum of amortized monthly stove cost and monthly fuel cost. The model I introduce below assumes initially that households do not have credit constraints restricting upfront fixed costs of acquiring new cooking technology. However, this assumption may not hold in some areas in India where households do not use clean stoves because the upfront stove cost is high relative to income, and loans are not available for consumer goods. In areas where credit constraints are a major barrier, the upfront stove cost may have a relatively higher effect compared to the monthly fuel cost due to the shadow value of credit. In such cases, policies such as promoting microfinance can help households adopt cleaner energy technologies. I show in the Appendix to this chapter that this shadow value of credit can be accommodated in the model.

Table 5-3. Determination of Predicted Kitchen IAP Mean Concentrations by Stove Type

Regression Variable	Coefficient	Standard Error	*t*-statistics	*p*-value
Energy Technology				
1—One Traditional Stove	1.071	0.001	1294.270	0.000
2—One Kerosene Stove	0.069	0.001	66.800	0.000
3—One LPG Stove	0.068	0.001	73.900	0.000
4—Both Primary and Secondary Stoves are Traditional	1.299	0.001	1339.300	0.000
5—Primary Stove is Traditional; Secondary Stove is Kerosene	1.049	0.001	1167.450	0.000
6—Primary Stove is Traditional; Secondary Stove is LPG	1.049	0.001	1201.860	0.000
7—Primary Stove is Kerosene; Secondary Stove is Traditional	0.341	0.001	305.880	0.000
8—Primary Stove is LPG; Secondary Stove is Traditional	0.339	0.001	370.780	0.000
Wall materials				
Mud wall	0.084	0.000	224.030	0.000
Ventilation condition (reference= poor ventilation				
Good ventilation	-0.513	0.000	-1244.550	0.000
Moderate ventilation	-0.164	0.000	-445.410	0.000
Kitchen location (reference= kitchen in living area)				
Separate kitchen inside house	-0.383	0.001	-753.010	0.000
External kitchen with outside door	-0.150	0.001	-271.410	0.000
External kitchen with inside and outside door	-0.074	0.001	-137.260	0.000
Outdoor kitchen	0.427	0.001	803.650	0.000
Detached enclosed kitchen	-0.027	0.001	-43.750	0.000
Cooking time	0.061	0.000	490.880	0.000
Household Size	0.049	0.000	654.960	0.000
Median temperature	0.026	0.000	481.930	0.000
Median humidity	-0.006	0.000	-317.420	0.000
State of Residence				
West Bengal	-0.395	0.001	-727.300	0.000
Madhya Pradesh	-0.430	0.001	-596.130	0.000
Tamil Nadu	-1.129	0.001	-1255.760	0.000
Constant	-2.080	0.002	-1107.100	0.000
Observations	494			
R^2 statistic	>0.995			

Table 5-4. Cleanliness (IAP Mean Concentrations) by Energy Technology

Choice	Energy Technology	IAP Mean Concentrations (mg/m^3)
1	One Traditional Stove	0.56
2	One Kerosene Stove	0.21
3	One LPG Stove	0.21
4	Both Primary and Secondary Stoves are Traditional	0.70
5	Primary Stove is Traditional; Secondary Stove is Kerosene	0.55
6	Primary Stove is Traditional; Secondary Stove is LPG	0.55
7	Primary Stove is Kerosene; Secondary Stove is Traditional	0.27
8	Primary Stove is LPG; Secondary Stove is Traditional	0.27
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.19

Source: Calculated as $Y_i = e^{\beta} Y_9$ where Y_9 = 0.19 mg/m^3, the average IAP mean concentration of the reference stove type (choice 9) and β is the corresponding coefficient in Table 5.3.

I estimate the stove cost and fuel cost for each energy technology as follows.

Stove Cost

Since stove prices are not included in the HEED survey data, I estimate the stove cost based on a variety of sources. I primarily rely on stove price and lifetime information from the discussion forum of biomass cooking stoves hosted by the Renewable Energy Policy Project (2008), after cross checking the information with Venkataraman (2008), Energy Sector Management Assistant Program (2003 and 2004), and Thiagu and Young (1989). Although some variations are expected for different stove models within each type of stove, both between rural and urban areas, and among states, I use the following stove prices and lifetime for estimation: traditional stove—25 Rs with a 2-year lifetime, kerosene stove—400 Rs with a 3-year lifetime, and LPG stove—2000 Rs with a 10-year lifetime. I use an annual discount rate of 12% (Venkataraman, 2008) to amortize stove cost over the stove lifetime to get a constant amortized monthly stove cost. When two stoves are used, the fixed cost of the energy technology choice is the sum of the two amortized stove costs. The amortized monthly fixed cooking costs are summarized in Table 5-5.

Table 5-5. Amortized Monthly Fixed Cooking Costs by Energy Technology

Choice	Energy Technology	Amortized Monthly Cost (Rs)
1	One Traditional Stove	1.23
2	One Kerosene Stove	13.88
3	One LPG Stove	29.50
4	Both Primary and Secondary Stoves are Traditional	2.47
5	Primary Stove is Traditional; Secondary Stove is Kerosene	15.11
6	Primary Stove is Traditional; Secondary Stove is LPG	30.73
7	Primary Stove is Kerosene; Secondary Stove is Traditional	15.11
8	Primary Stove is LPG; Secondary Stove is Traditional	30.73
9	Primary Stove is LPG; Secondary Stove is Kerosene	43.38

Source: Calculated as the amortized cost of ownership assuming a 12% discount rate where traditional, kerosene, and LPG stoves cost 25, 400, and 2000 Rs and have lifetimes of 2, 3, and 10 years, respectively.

Fuel Cost

I use the following steps to estimate the operating cost of each energy technology: (a) collect fuel price information from the survey, (b) convert the fuel price into a uniform energy price unit (Rs/MJ) by applying for an energy content factor, and (c) calculate the required monthly fuel cost of each energy technology that meets average household cooking needs.[6]

Most cooking fuels are available at local markets. For kerosene and LPG stoves, households buy kerosene and LPG from the market. For traditional stoves, the most commonly used cooking fuels are firewood, dung cakes, and crop residue. About a third of households buy traditional cooking fuels directly from the market as well. Others collect them for free. However, when the traditional biomass is free, considerable time and effort is required to collect it. The opportunity cost of this time and effort in collecting fuels is reflected by market fuel prices under competitive conditions.

The IHDS village survey includes the market price for firewood, dung cakes, kerosene, and LPG. Because the IHDS village level data cannot be matched with the HEED data, I aggregate the fuel price data at the state level as shown in Table 5-6. As expected, prices vary

[6] For notational purposes, "MJ" stands for "mega joule."

among states. In particular, Madhya Pradesh has a relatively high kerosene price compared to the other three states. This may reflect a kerosene shortage experienced by Madhya Pradesh in 2005 during which the survey was conducted.[7] Nevertheless, fuel prices among the states are generally comparable and clean fuel prices are much higher than solid fuel prices.

Table 5-6. Market Prices for Cooking Fuels

Fuel Price	Unit	Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
Firewood	Rs/kg	1.81	1.25	1.35	1.96
Dung	Rs/kg	2.55	1.22	0.80	1.99
Kerosene	Rs/liter	12.44	11.00	21.42	15.76
LPG	Rs/kg	15.80	22.65	22.07	21.76

Source: IHDS Village Survey Data

To convert fuel prices in Table 5-6 into a uniform energy price unit, I use energy content factors from Habib, et al. (2004). These values are consistent with those reported by the International Network for Sustainable Energy (2006). The results are shown in Table 5-7. Because clean fuels have much higher energy content than solid fuels, the price differences between clean and solid fuels are not so dramatic after converting into a uniform energy price unit, although clean fuel prices are still 3-7 times higher than solid fuels.

Table 5-7. Cooking Fuel Prices in MJ/kg

Cooking Fuel	Energy Content Factor (MJ/kg)[a]	Fuel Price (Rs/MJ)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
Firewood	16.2	0.11	0.08	0.08	0.12
Dung	11.8	0.22	0.10	0.07	0.17
Kerosene[b]	42.6	0.36	0.31	0.61	0.45
LPG	45.9	0.34	0.49	0.48	0.47

[a] Source: Habib, et al. (2004).
[b] Kerosene has a density of 0.82 kg/liter.

To estimate monthly cooking cost of each energy technology, I first estimate the unit fuel cost for each energy technology. For this purpose, I assume that a traditional stove uses

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[7] See, for example, the news story, "Kerosene shortage hits central India, MP sounds alarm" http://www.financialexpress.com/news/kerosene-shortage-hits-central-india-mp-sounds-alarm/139372/ accessed on March 12, 2009.

70% firewood and 30% dung based on the post monitoring data that shows an average household using a primary traditional stove consumes 1260 MJ of energy from firewood and 480 MJ of energy from dung. I further assume that if both a primary and a secondary stove are used, the primary stove provides 80% of cooking energy and the secondary stove provides 20%. Applying these assumptions to Table 5-7, Table 5-8 shows unit fuel cost by energy technology. Finally, based on the information from Venkataraman (2008) on annual household cooking energy usage in India, I assume that 1570 MJ cooking energy is required for an average household per month. By applying this figure to Table 5-8, Table 5-9 shows monthly fuel cost for each energy technology. This is the estimate of monthly fuel cost for an average household and will vary by factors such as household size and access to clean fuel and the particular biomass fuel. I control for these variations in later regressions.

The total cooking cost is then the sum of the amortized stove cost and the monthly fuel cost. The total cooking cost by energy technology is shown in Table 5-10.

Table 5-8. Unit Fuel Cost (Rs/MJ) by Energy Technology

Choice	Energy Technology	Fuel Cost (Rs/MJ)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
1	One Traditional Stove	0.14	0.09	0.08	0.14
2	One Kerosene Stove	0.36	0.31	0.61	0.45
3	One LPG Stove	0.34	0.49	0.48	0.47
4	Both Primary and Secondary Stoves are Traditional	0.14	0.09	0.08	0.14
5	Primary Stove is Traditional; Secondary Stove is Kerosene	0.19	0.13	0.19	0.20
6	Primary Stove is Traditional; Secondary Stove is LPG	0.18	0.17	0.16	0.20
7	Primary Stove is Kerosene; Secondary Stove is Traditional	0.31	0.27	0.51	0.39
8	Primary Stove is LPG; Secondary Stove is Traditional	0.30	0.41	0.40	0.41
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.35	0.46	0.51	0.47

Source: Calculated from Table 5.7 assuming a traditional stove uses 70% firewood and 30% dung, and that the primary stove provides 80% of cooking energy and the secondary stove provides 20% when two stoves are used.

Table 5-9. Monthly Fuel Cost (Rs/MJ) by Energy Technology

Choice	Energy Technology	Monthly Fuel Cost (Rs/month)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
1	One Traditional Stove	224	134	124	212
2	One Kerosene Stove	559	494	963	708
3	One LPG Stove	540	775	755	744
4	Both Primary and Secondary Stoves are Traditional	224	134	124	212
5	Primary Stove is Traditional; Secondary Stove is Kerosene	291	206	292	311
6	Primary Stove is Traditional; Secondary Stove is LPG	287	262	250	319
7	Primary Stove is Kerosene; Secondary Stove is Traditional	492	422	795	609
8	Primary Stove is LPG; Secondary Stove is Traditional	477	647	629	638
9	Primary Stove is LPG; Secondary Stove is Kerosene	544	719	796	737

Source: Calculated from Table 5.8 assuming an average household requires 1570 MJ cooking energy per month following Venkataraman (2008).

Table 5-10. Total Monthly Cooking Cost (Rs/month) by Energy Technology

Choice	Energy Technology	Monthly Cooking Cost (Rs/month)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
1	One Traditional Stove	225	135	125	213
2	One Kerosene Stove	573	508	977	722
3	One LPG Stove	570	804	784	774
4	Both Primary and Secondary Stoves are Traditional	227	136	126	215
5	Primary Stove is Traditional; Secondary Stove is Kerosene	306	221	307	326
6	Primary Stove is Traditional; Secondary Stove is LPG	318	293	281	349
7	Primary Stove is Kerosene; Secondary Stove is Traditional	507	437	810	624
8	Primary Stove is LPG; Secondary Stove is Traditional	508	677	659	668
9	Primary Stove is LPG; Secondary Stove is Kerosene	587	762	840	780

Source: Calculated from Tables 5.5 and 5.9.

The Estimated Model

I assume that a household has a utility function over cooking service and the numeraire, which represents all other goods with a unit price, and the quality attributes of the chosen energy technology. Household utility functions differ by household characteristics. Thus, households base their technology choices on the associated quality attributes, but the value placed on these attributes varies with households.

Household income plays an important role in making the stove choice because stoves are long-term investments. Because the income effect can be important when the fixed stove cost is a major household expense in selecting the energy technology choice, I forego the common assumption whereby income does not interact with the cost of technology in determining the technology choice. To represent this interaction, I assume that cooking cost detracts from the income available for expenditure on all other goods, and utility is concave in the expenditure on all other goods as approximated by a quadratic form.

Specifically, this motivates a representation for the indirect utility function of household *n* when choosing energy technology *j* ($j = 1,\ldots,9$) given by

(5-1) $$V_{nj} = v_{nj} + \varepsilon_{nj} = \alpha_1(y - p_j) + \alpha_2(y - p_j)^2 + \boldsymbol{\beta} \cdot \mathbf{w_n} \cdot \mathbf{q_j} + \gamma_j + \boldsymbol{\omega}_\mathbf{j} \cdot \mathbf{z_n} + \varepsilon_{nj}$$

where v_{nj} is the non-random component of utility as defined implicitly by the equation, y is monthly household income, p_j is the monthly cooking cost for choice *j*, $\mathbf{w_n}$ is a vector of the observed household characteristics that affect the households' valuation of energy technology attributes, $\mathbf{q_j}$ is a vector of energy technology attributes for choice *j*, $\mathbf{z_n}$ represents other observed household characteristics, ε_{nj} is an unobserved extreme value random term with a zero mean, and α_1, α_2, $\boldsymbol{\beta}$, γ_j, and $\boldsymbol{\omega}_\mathbf{j}$ are parameters to be estimated.

Different discrete choice models can be used to estimate the parameters depending on assumptions. Several possibilities based on the assumed extreme value distribution are the simple logit, nested logit, and mixed logit models.

The simple logit model is the simplest and most widely used discrete choice model by far. This model assumes that all parameters are fixed and the error terms are distributed identically and independently (iid) with type I extreme value distributions. As shown in McFadden (1974), under these assumptions, the probability that household *n* chooses stove type *i* is

(5-2) $$P_{nj} = \frac{e^{v_{nj}}}{\sum_{l=1}^{J} e^{v_{nl}}}.$$

The advantage of using the simple logit model is that this formula is a closed form that is easy to estimate and interpret. However, a limitation is that it implies proportional substitution across alternatives, namely, *independence from irrelevant alternatives* (IIA). While the IIA property provides an accurate representation of reality in some settings, it is not appropriate in others. The most famous example is the red-bus-blue-bus problem. If alternatives can be partitioned into subsets or nests, the nested logit model and test may be more appropriate.

The nested logit model is often appropriate when choices are made in nests. In the case of energy technology choices, as shown in Figure 5.1, households may first choose how many stoves they would like to have and then consider what type of stoves to use. Alternatively, they may first choose a primary stove and then decide whether to obtain another stove. The nested logit model assumes all parameters are fixed, but the error terms have generalized extreme value (GEV) distributions. For any two alternatives that are in the same nest, the ratio of probabilities is independent of the existence of all other alternatives. That is, IIA must hold within each nest. For any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. Thus, IIA does not hold in general for alternatives in different nests.

If the household first chooses how many stoves to use and then which stoves to acquire, the probability that household *n* chooses energy technology *j* is

(5-3)
$$P_{nj} = \frac{e^{v_{nj}/\lambda_1}\left(\sum_{l=1}^{3} e^{v_{nl}/\lambda_1}\right)^{\lambda_1 - 1}}{\left(\sum_{l=1}^{3} e^{v_{nl}/\lambda_1}\right)^{\lambda_1 - 1} + \left(\sum_{l=4}^{9} e^{v_{nl}/\lambda_2}\right)^{\lambda_2 - 1}},\ j = 1,2,3$$

$$P_{nj} = \frac{e^{v_{nj}/\lambda_2}\left(\sum_{l=1}^{3} e^{v_{nl}/\lambda_2}\right)^{\lambda_2 - 1}}{\left(\sum_{l=1}^{3} e^{v_{nl}/\lambda_1}\right)^{\lambda_1 - 1} + \left(\sum_{l=4}^{9} e^{v_{nl}/\lambda_2}\right)^{\lambda_2 - 1}},\ j = 4,\ldots,9$$

where $1 - \lambda_1$ is a measure of error term correlation among the first nest (among ε_{n1}, ε_{n2}, and ε_{n3}) and $1 - \lambda_2$ is a measure of error term correlation among the second nest (among $\varepsilon_{n4}, \ldots, \varepsilon_{n9}$). If $\lambda_1 = 1$ (or $\lambda_2 = 1$), indicating no correlation among the unobserved components of utility for alternatives within the first (or second) nest, then the choice probabilities follow the simple logit model.

The simple logit model and nested logit model can represent taste variation if tastes vary systematically with observed variables. However, if taste variation is at least partly random, these logit models are misspecified. As Train (2003) argued, simple logit models might be able to provide an adequate approximation of average tastes even when tastes are random because the simple logit formula seems to be fairly robust to misspecification. However, simple logit models may be applied in situations where they will not approximate average tastes. To incorporate random taste variation appropriately and fully, a mixed logit model can be useful.

With the mixed logit model, at least one of the parameters is assumed to be a random parameter and the error terms are assumed to have iid type I extreme value distributions. The probability that household *n* chooses stove type *j* becomes the integral of standard logit probabilities over a density of parameters that can be expressed as

(5-4) $$P_{nj} = \int \frac{e^{v_{nj}}}{\sum_{l=1}^{J} e^{v_l}} f(\varphi_n) d\varphi_n$$

where φ_n is a vector of estimated coefficients and $f(\varphi_n)$ is the probability density function. If φ_n is a vector of fixed parameters, then the mixed logit model becomes a simple logit model.

The log-likelihood function is

(5-5) $$LL(\varphi) = \sum_{n=1}^{N} \sum_{j=1}^{J} \ln \left(\int \frac{e^{v_{nj}}}{\sum_{l=1}^{J} e^{v_l}} f(\varphi_n) d\varphi_n \right)^{S_{nj}}$$

where

$$S_{nj} = \begin{cases} 1 & \text{for the chosen alternative } j, \\ 0 & \text{otherwise.} \end{cases}$$

The mixed logit model, unlike the simple and nested logit models, generally does not have a closed form solution for the integration in equation (4). Therefore, maximum simulated likelihood estimation is a typical method used to estimate the mixed logit model.

Empirical Specification and Results

This section reports estimates using the simple, nested, and mixed logit models to estimate the coefficient vector φ_n. The household characteristics $\mathbf{z_n}$ that enter into the coefficients for choice specific constants include a dummy variable for living in an urban area, a dummy variable of owning a farm, and household size. Clean fuels are likely easier to access and traditional biomass fuels are likely more expensive to obtain for households in an urban area. Thus, urban households are more likely to choose clean stoves such as kerosene or LPG stoves. Similarly, households who own a farm likely spend less effort collecting biomass fuel. Thus, rural households are more likely to choose traditional stoves. It is not clear how household size affects household energy technology choices. As household size increases, per capita cooking fuel use likely decreases due to economics of scale, but overall fuel use likely increases, which may make switching to clean fuels harder.

Household valuations of different stove attributes likely depend on their characteristics. Household income likely plays an important role in selecting stove choices because stoves are long-term investments. As specified in equation (5-1), cooking cost detracts from the income available for expenditure on all other goods (as represented by $y - p_j$) and utility is assumed to be concave in the expenditure on all other goods as approximated by a quadratic form.

For preferences related to cooking time, the wage rate of unskilled labor by women is likely the major determinant. Cooking is usually done by women. In a majority of cases, the wage rate for unskilled labor by women likely reflects the opportunity cost of women’s time. A higher wage rate thus most likely causes a household to choose an energy technology that reduces cooking time. The wage rate data is derived from the village survey in IHDS. Again, I aggregate the village level wage rates to the state level as shown in Table 5-11.

Table 5-11. Wage Rate of Unskilled Labor (Rs/Day)

Labor Category	Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
Men	78	43	49	93
Women	56	38	45	48
Children under 15	50	26	39	40

Source: IHDS data.

For the pollution level, understanding of the health effects of cooking smoke is key. A dummy variable is used to indicate the belief that cooking smoke is harmful to health. If a household knows that cooking smoke is harmful to health, it is likely to prefer a less polluting stove. The limitation associated with using this variable is that it potentially introduces endogeneity. For example, it could be that households who buy LPG stoves are educated by the sellers about IAP when they buy the stove. If so, then awareness of IAP may be an endogenous indicator that explains buying LPG stoves. However, I do not expect that this is a serious problem because clean stove sellers generally do not go to villages to educate people and most people (over 90%) in the sample indicate that they are aware of IAP already. Another limitation of using this variable is that it is a dummy variable. Thus, it does not identify how harmful households believe IAP is. There can be a wide variation of how seriously households consider IAP's health impact among those who believe cooking smoke is harmful. However, more detailed information on health beliefs is simply not available in this dataset.

The summary statistics for the variables used in estimation are presented in Table 5-12.

Table 5-12. Summary Statistics of Variables Explaining Cooking Technology Choice

Variable	Mean	Standard Deviation	Minimum	Maximum
Stove Attributes				
Cooking Cost (Hundred Rs/month)	4.85	2.48	1.25	9.77
Cooking Time (Hour)	2.94	0.36	2.46	3.51
Pollution Level (mg/m^3)	0.39	0.19	0.19	0.70
Household Characteristics				
Monthly Income (Hundred Rs)	43.75	35.57	6.22	276.03
Unskilled Women Hourly Wage (Rs/hour)	5.82	6.41	4.75	7.00
Health Belief (dummy)	0.93	0.25	0	1
Urban (dummy)	0.33	0.47	0	1
Own a Farm (dummy)	0.39	0.49	0	1
Household Size	5.19	2.06	1	15
Number of Households	499			

The energy technology choice model parameters are estimated in Table 5-13. Although estimation of various nested structures was attempted, convergence could not be achieved. Based on the best fit that could be achieved (a specification without interaction terms between household size and choice variables), the hypothesis of no nesting could not be rejected. Thus, only the results of using a simple logit model and a mixed logit model are presented in columns

Table 5-13. Stove Choice Estimation with Simple Logit and Mixed Logit Models[a]

Regression Variables	(I) Simple Logit Estimated Coefficient	(I) Simple Logit Standard Error	(II) Mixed Logit[b] Estimated Coefficient	(II) Mixed Logit[b] Standard Error
Income-Cooking Cost	0.004***	0.001	0.004***	0.001
Standard Deviation			0.009	0.027
Square of (Income-Cooking Cost)	-3.49E-7***	4.8E-08	-3.5E-7***	1E-08
Standard Deviation			0.000	3.00E-04
Cooking Time*Unskilled Women Wage	-0.156	0.208	-0.1432	0.0154
Standard Deviation			0.015	0.024
IAP*Health Belief	-4.455**	1.888	-4.659**	0.2164
Standard Deviation			0.249	0.350
Choice1	3.396*	1.906	3.354*	1.9234
Choice2	2.507*	1.437	2.521*	1.4438
Choice3	1.489	1.162	1.4007	1.1423
Choice4	0.894	1.790	0.8802	1.8081
Choice5	1.889	1.579	1.9009	1.5831
Choice6	1.168	1.844	1.0544	1.8621
Choice7	1.719	1.286	1.7233	1.2853
Choice8	1.337	1.131	1.2048	1.1179
Choice 1*Urban	-2.646***	0.864	-2.568***	0.131
Choice 2*Urban	-1.037	1.019	-0.987	0.619
Choice 3*Urban	-1.132	0.937	-1.075	0.027
Choice 4*Urban	-2.896***	0.950	-2.838***	0.573
Choice 5*Urban	-1.030	0.904	-0.972	0.048
Choice 6*Urban	-2.280**	0.927	-2.561**	1.216
Choice 7*Urban	-2.592***	0.973	-2.519***	0.201
Choice 8*Urban	-2.059**	0.925	-1.999**	0.247
Choice 1*Farm	1.520	1.198	1.785	0.138
Choice 2*Farm	-13.261	671.763	-4.022	0.285
Choice 3*Farm	0.252	1.292	0.469	0.100
Choice 4*Farm	0.921	1.249	1.201	0.058
Choice 5*Farm	2.494**	1.223	2.693**	0.323
Choice 6*Farm	2.890**	1.224	3.265**	0.171
Choice 7*Farm	-0.409	1.409	-0.174	0.143
Choice 8*Farm	1.578	1.225	1.840	0.023
Choice 1*Household Size	0.397**	0.162	0.398**	0.011
Choice 2*Household Size	-0.302	0.252	-0.338	0.029
Choice 3*Household Size	-0.006	0.169	0.002	0.024
Choice 4*Household Size	0.618***	0.172	0.621***	0.023
Choice 5*Household Size	0.206	0.172	0.207	0.005
Choice 6*Household Size	0.470	0.165	0.466	0.001
Choice 7*Household Size	0.090	0.208	0.058	0.086
Choice 8*Household Size	0.158	0.166	0.171	0.032
Observations	4491		4491	
Log Likelihood	-780.416		-770.189	

[a] The *p*-values are indicated by '***' for p<0.01, '**' for p<0.05, and '*' for p<0.10.

[b] Choice 1 to Choice 8 have fixed parameters and the other variables have random parameters with a normal distribution. The estimated standard deviations for the interaction terms between choice alternatives and urban, farm, and household size variables are not shown in the Table.

(I) and (II) of Table 5-13, respectively. Household fixed effects are applied to each model to control for household unobservables.

Stove choice 9 (the primary stove is LPG and the secondary stove is kerosene) is the reference stove type. The estimated coefficients of the simple logit model in column (I) all have the expected signs. The estimated utility function is concave in income available for expenditure on other goods as expected, and the coefficients are statistically significant at the 1% level. This means that the marginal utility of income decreases as income increases. Thus, households are less sensitive to cooking cost as income increases.

For cooking time, households are more likely to choose energy technologies with shorter cooking time in areas with higher wage rates for unskilled women. However, this coefficient is not statistically significant. For the pollution level, households that know IAP is harmful to health are more likely to choose energy technologies with lower pollution levels, and this effect is statistically significant at the 5% level. In addition, the results show that households living in urban areas are less likely to use a traditional stove and households owning a farm are more likely to use a traditional stove. Larger households are more likely to use only traditional stoves and this effect is statistically significant.

Column (II) in Table 5-13 is estimated using the mixed logit model assuming a normal distribution for the integration in equation (5-4).[8] The estimated coefficients in column (II) are very similar to the estimates using the simple logit model. In fact, using the likelihood ratio chi-square test, the hypothesis that these estimates are the same as the estimates using the simple logit model cannot be rejected. Testing equality of column (I) to column (II) yields a χ^2 statistic of 20.45 with 36 degrees of freedom implying a *p*-value of 0.9826. In fact, the

[8] Train's (2006) Matlab codes were adopted for nested logit and mixed logit estimation.

estimated standard deviations for the random variables are very small and not statistically significant, indicating that not much random taste variation exists in the population. Thus, the simple logit model works well to capture taste variations.

Using the estimates of Column (I) in Table 5-13, I can estimate and compare how different factors would affect household energy technology choices. Although switching to clean fuels is the most effective way to reduce IAP exposures, high stove and fuel costs are major barriers to adoption of clean energy technologies for households, especially in rural areas. Therefore, I consider how LPG stove cost, fuel cost, and income level would affect household choices of clean energy technologies.

First, Table 5-14 considers the case where the cost of an LPG stove declines by 50%. This might be accomplished by direct government subsidies or, to a lesser extent, through mass production and technology advancement. Results show that a dramatic reduction in the cost of clean stoves does little to change households' energy technology choice. The probability that an average rural household would change its primary stove from a traditional stove to a clean stove only increases between 0.1% and 0.3%. Tamil Nadu estimates indicate the highest change of 0.3%.

Second, Table 5-15 considers the case where the LPG fuel price increases by 40% since the LPG fuel price is currently highly subsidized and the Indian government is considering phasing out the subsidy. In this case, the LPG price increase would only slightly increase the use of traditional fuels. The probability that an average rural household would change to a traditional primary stove from a clean primary stove is between 0.1% and 3.1%. In terms of state of residence, phasing out the LPG subsidy has more noticeable impacts in Madhya Pradesh and Tamil Nadu than in Uttarakhand and West Bengal.

Table 5-14. Change in Energy Technology Choice Probabilities for an Average Rural Household if LPG Stove Cost is Reduced by 50%.

Choice	Energy Technology	Uttarakhand			West Bengal		
		Before	After	Change	Before	After	Change
1	One Traditional Stove	40.0%	39.8%	-0.3%	48.1%	47.9%	-0.2%
2	One Kerosene Stove	0.3%	0.3%	0.0%	2.0%	2.0%	0.0%
3	One LPG Stove	2.5%	2.6%	0.0%	4.4%	4.5%	0.0%
4	Both Primary and Secondary Stoves are Traditional	7.2%	7.2%	0.0%	9.6%	9.6%	0.0%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	11.6%	11.5%	-0.1%	6.9%	6.9%	0.0%
6	Primary Stove is Traditional; Secondary Stove is LPG	25.2%	25.5%	0.2%	14.2%	14.3%	0.1%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.7%	1.7%	0.0%	5.2%	5.2%	0.0%
8	Primary Stove is LPG; Secondary Stove is Traditional	10.9%	11.0%	0.1%	8.8%	8.8%	0.0%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.4%	0.4%	0.0%	0.8%	0.8%	0.0%
Having a clean stove as a primary stove		15.9%	16.0%	0.1%	21.3%	21.3%	0.1%
Choice	**Energy Technology**	**Madhya Pradesh**			**Tamil Nadu**		
		Before	**After**	**Change**	**Before**	**After**	**Change**
1	One Traditional Stove	55.5%	55.0%	-0.5%	51.9%	51.5%	-0.4%
2	One Kerosene Stove	0.4%	0.4%	0.0%	1.8%	1.8%	0.0%
3	One LPG Stove	1.9%	1.9%	0.1%	4.0%	4.1%	0.1%
4	Both Primary and Secondary Stoves are Traditional	7.8%	7.7%	-0.1%	9.5%	9.5%	-0.1%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	10.4%	10.3%	-0.1%	7.9%	7.8%	-0.1%
6	Primary Stove is Traditional; Secondary Stove is LPG	16.4%	16.8%	0.5%	11.4%	11.7%	0.3%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.6%	1.6%	0.0%	5.3%	5.3%	0.0%
8	Primary Stove is LPG; Secondary Stove is Traditional	5.8%	6.0%	0.2%	7.4%	7.5%	0.2%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.3%	0.3%	0.0%	0.8%	0.8%	0.0%
Having a clean stove as a primary stove		10.0%	10.2%	0.2%	19.3%	19.5%	0.3%

Third, Table 5-16 considers the case where the 50% reduction in the cost of an LPG stove is accompanied by 10% increase in household income. In this case, the probability that an average rural household would switch to a clean primary stove is between 1.3% and 2.3%. The probability of change of 2.3% is estimated for West Bengal. Comparing to the case in Table 5-14, it seems that households' energy technology choices are more responsive to income changes.

Finally, Table 5-17 considers the case where household income is doubled. These results show that an average rural household would have a considerably higher probability of

Table 5-15. Change in Energy Technology Choice Probabilities for an Average Rural Household if LPG Fuel Price Increases by 40%

Choice	Energy Technology	Uttarakhand			West Bengal		
		Before	After	Change	Before	After	Change
1	One Traditional Stove	40.0%	41.1%	1.0%	48.1%	49.3%	1.2%
2	One Kerosene Stove	0.3%	0.4%	0.0%	2.0%	2.1%	0.1%
3	One LPG Stove	2.5%	2.5%	0.0%	4.4%	4.9%	0.5%
4	Both Primary and Secondary Stoves are Traditional	7.2%	7.3%	0.1%	9.6%	9.7%	0.1%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	11.6%	11.8%	0.2%	6.9%	7.0%	0.1%
6	Primary Stove is Traditional; Secondary Stove is LPG	25.2%	24.4%	-0.8%	14.2%	12.9%	-1.3%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.7%	1.7%	0.0%	5.2%	5.3%	0.1%
8	Primary Stove is LPG; Secondary Stove is Traditional	10.9%	10.4%	-0.5%	8.8%	8.2%	-0.6%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.4%	0.4%	0.0%	0.8%	0.7%	-0.1%
Having a clean stove as a primary stove		15.9%	15.4%	-0.5%	21.3%	21.2%	-0.1%
Choice	**Energy Technology**	**Madhya Pradesh**			**Tamil Nadu**		
		Before	**After**	**Change**	**Before**	**After**	**Change**
1	One Traditional Stove	55.5%	58.5%	2.9%	51.9%	54.9%	3.0%
2	One Kerosene Stove	0.4%	0.4%	0.0%	1.8%	1.9%	0.1%
3	One LPG Stove	1.9%	1.1%	-0.8%	4.0%	2.9%	-1.1%
4	Both Primary and Secondary Stoves are Traditional	7.8%	8.1%	0.4%	9.5%	10.0%	0.5%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	10.4%	10.9%	0.5%	7.9%	8.3%	0.4%
6	Primary Stove is Traditional; Secondary Stove is LPG	16.4%	15.1%	-1.2%	11.4%	10.6%	-0.8%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.6%	1.7%	0.1%	5.3%	5.6%	0.3%
8	Primary Stove is LPG; Secondary Stove is Traditional	5.8%	4.0%	-1.8%	7.4%	5.3%	-2.1%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.3%	0.2%	-0.1%	0.8%	0.6%	-0.2%
Having a clean stove as a primary stove		10.0%	7.4%	-2.6%	19.3%	16.2%	-3.1%

Table 5-16. Change in Energy Technology Choice Probabilities for an Average Rural Household if LPG Stove Cost is Reduced by 50% and Income increases by 10%.

Choice	Energy Technology	Uttarakhand			West Bengal		
		Before	After	Change	Before	After	Change
1	One Traditional Stove	40.0%	38.8%	-1.3%	48.1%	46.2%	-1.8%
2	One Kerosene Stove	0.3%	0.3%	0.0%	2.0%	2.1%	0.1%
3	One LPG Stove	2.5%	2.8%	0.3%	4.4%	5.3%	0.9%
4	Both Primary and Secondary Stoves are Traditional	7.2%	7.0%	-0.2%	9.6%	9.3%	-0.4%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	11.6%	11.5%	-0.1%	6.9%	6.7%	-0.1%
6	Primary Stove is Traditional; Secondary Stove is LPG	25.2%	25.5%	0.2%	14.2%	14.1%	0.0%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.7%	1.8%	0.1%	5.2%	5.4%	0.2%
8	Primary Stove is LPG; Secondary Stove is Traditional	10.9%	11.8%	0.9%	8.8%	9.8%	1.1%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.4%	0.5%	0.0%	0.8%	0.9%	0.1%
Having a clean stove as a primary stove		15.9%	17.2%	1.3%	21.3%	23.6%	2.3%
Choice	**Energy Technology**	**Madhya Pradesh**			**Tamil Nadu**		
		Before	**After**	**Change**	**Before**	**After**	**Change**
1	One Traditional Stove	55.5%	53.8%	-1.7%	51.9%	50.1%	-1.8%
2	One Kerosene Stove	0.4%	0.4%	0.0%	1.8%	2.0%	0.1%
3	One LPG Stove	1.9%	2.2%	0.3%	4.0%	4.5%	0.6%
4	Both Primary and Secondary Stoves are Traditional	7.8%	7.5%	-0.2%	9.5%	9.2%	-0.3%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	10.4%	10.4%	0.0%	7.9%	7.8%	-0.1%
6	Primary Stove is Traditional; Secondary Stove is LPG	16.4%	16.9%	0.5%	11.4%	11.7%	0.3%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.6%	1.8%	0.2%	5.3%	5.7%	0.3%
8	Primary Stove is LPG; Secondary Stove is Traditional	5.8%	6.6%	0.8%	7.4%	8.1%	0.8%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.3%	0.4%	0.1%	0.8%	0.9%	0.1%
Having a clean stove as a primary stove		10.0%	11.4%	1.4%	19.3%	21.2%	1.9%

adopting a clean stove. The probability of switching to a clean stove as the primary stove increases between 14% and 24% for rural households with the highest likelihood of change occurring in West Bengal. This analysis implies that large scale switching to clean fuels in rural India is unlikely to occur without substantial increases in household income. This result is consistent with the conclusions in Zhang et al (2007) and Zhang and Vanneman (2008) that fuel switching on a large scale will not occur until rural areas have seen a substantial amount of development.

Table 5-17. Change in Energy Technology Choice Probabilities for an Average Rural Household if Income is Doubled.

Choice	Energy Technology	Uttarakhand			West Bengal		
		Before	**After**	**Change**	**Before**	**After**	**Change**
1	One Traditional Stove	40.0%	29.6%	-10.4%	48.1%	31.7%	-16.4%
2	One Kerosene Stove	0.3%	0.4%	0.1%	2.0%	2.7%	0.7%
3	One LPG Stove	2.5%	5.9%	3.3%	4.4%	15.4%	11.0%
4	Both Primary and Secondary Stoves are Traditional	7.2%	5.4%	-1.9%	9.6%	6.2%	-3.4%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	11.6%	10.5%	-1.1%	6.9%	5.1%	-1.7%
6	Primary Stove is Traditional; Secondary Stove is LPG	25.2%	24.7%	-0.5%	14.2%	12.0%	-2.2%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.7%	2.7%	1.0%	5.2%	6.2%	1.0%
8	Primary Stove is LPG; Secondary Stove is Traditional	10.9%	19.6%	8.8%	8.8%	18.4%	9.7%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.4%	1.1%	0.7%	0.8%	2.2%	1.4%
Having a clean stove as a primary stove		15.9%	29.8%	13.9%	21.3%	45.0%	23.7%
Choice	**Energy Technology**	**Madhya Pradesh**			**Tamil Nadu**		
		Before	**After**	**Change**	**Before**	**After**	**Change**
1	One Traditional Stove	55.5%	42.4%	-13.1%	51.9%	37.6%	-14.3%
2	One Kerosene Stove	0.4%	1.2%	0.8%	1.8%	3.6%	1.7%
3	One LPG Stove	1.9%	5.3%	3.5%	4.0%	9.9%	6.0%
4	Both Primary and Secondary Stoves are Traditional	7.8%	6.0%	-1.8%	9.5%	6.9%	-2.6%
5	Primary Stove is Traditional; Secondary Stove is Kerosene	10.4%	10.5%	0.1%	7.9%	7.0%	-0.9%
6	Primary Stove is Traditional; Secondary Stove is LPG	16.4%	15.9%	-0.5%	11.4%	10.8%	-0.6%
7	Primary Stove is Kerosene; Secondary Stove is Traditional	1.6%	4.7%	3.1%	5.3%	8.5%	3.1%
8	Primary Stove is LPG; Secondary Stove is Traditional	5.8%	12.9%	7.1%	7.4%	13.6%	6.3%
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.3%	1.1%	0.8%	0.8%	2.0%	1.2%
Having a clean stove as a primary stove		10.0%	25.3%	15.3%	19.3%	37.6%	18.3%

Conclusions

In this chapter, I have applied a novel approach to model household behavior regarding energy technology choices. I assume that households choose a cooking energy technology based on its attributes: cooking cost, convenience, and cleanliness. Cooking cost includes amortized stove cost and fuel cost. Convenience is measured by cooking time, and cleanliness is measured as IAP levels. I assume these attributes do not vary among households, but that household valuation of these attributes depends on household characteristics. Because the income effect plays an important role in selecting energy technology choices, I use a form that models the utility of income available for expenditure on other goods, which implicitly assumes that cooking services are separable from all other goods in utility.

Results show that the marginal utility of income decreases as income increases and that this effect carries over into the cooking technology choice. Thus, households are less sensitive to cooking cost as income increases. Results also show that women's opportunity cost of time affects households' valuation of the convenience of cooking energy technologies. Households are more likely to choose energy technologies with shorter cooking time in areas with higher wage rates for unskilled women, although this effect is not statistically significant. With respect to cleanliness, results show that households that know IAP is harmful to health are more likely to choose energy technologies with lower pollution levels.

The estimated model has important implications regarding what policy measures are likely to cause a significant increase in use of clean cooking technology. Results imply that rural households barely respond to a large 50% subsidy on LPG stoves and only slightly increase the use of clean stoves with a 10% increase in income in addition to a 50% subsidy of LPG stoves. On the other hand, rural households are not very responsive to a substantial LPG price increase, such as might be the result of discontinuing LPG subsidies. The probability of switching from a clean primary stove to a traditional primary stove is between 0.1% and 3.1% if LPG price increases by 40%. Rural households appear to be more responsive to income changes, but a major improvement in income is required to substantially improve IAP levels. If income is doubled, 14%-24% of rural households would switch their primary stove from a traditional stove to a clean stove. This analysis confirms that fuel switching on a large scale will not occur in rural areas unless substantial development occurs in India's rural economies.

By quantifying the factors that affect households' energy technology choices, the estimation results from this chapter provide the basis for economic welfare evaluation associated with alternative policy interventions in the next chapter.

Appendix to Chapter 5

How the Shadow Value of Credit Can Be Accommodated in the Model

Equation (5-1) can be rewriten as follows by adding an inconsequential constant term:

$$\boldsymbol{V_{nj}} = \boldsymbol{v_{nj}} + \varepsilon_{\boldsymbol{nj}} = \alpha_0 + \alpha_1(\boldsymbol{y} - \boldsymbol{p_j}) + \alpha_2(\boldsymbol{y} - \boldsymbol{p_j})^2 + \boldsymbol{\beta} \cdot \mathbf{w_n} \cdot \mathbf{q_j} + \gamma_{\boldsymbol{nj}} + \boldsymbol{\omega}_{\mathbf{nj}} \cdot \mathbf{z_n} + \varepsilon_{\boldsymbol{nj}}\,\textbf{.}$$

To see that this model can accommodate a shadow value of credit for poor households, let $\bar{p}_j = p_j + s_j$ where p_j is as defined in equation (5-1) and s_j represents an additional shadow value associated with a credit constraint that restricts financing of the fixed cost of technology. If s_j is non-zero, then the first three right-hand terms of the utility specification become

$$\begin{aligned}
&\alpha_0 + \alpha_1(y - \bar{p}_j) + \alpha_2(y - \bar{p}_j)^2 \\
&\qquad = \alpha_0 + \alpha_1(y - p_j - s_j) + \alpha_2(y - p_j - s_j)^2 \\
&\qquad = \alpha_0 + \alpha_1(y - p_j) + \alpha_2(y - p_j)^2 - \alpha_1 s_j - 2\alpha_2 s_j(y - p_j) + \alpha_2 s_j^2.
\end{aligned}$$

This implies that the additional shadow value effect of a credit constraint simply adds the term $\alpha_2 s_j^2 - \alpha_1 s_j - 2\alpha_2 s_j(y - p_j)$ to the utility specification for the logit estimation. If a variable were available to measure the intensity of the credit constraint, then this variable could be used in place of s_j to estimate the model and test for the effect of a credit constraint.

Alternatively, if the shadow value of a credit constraint is a linearly decreasing function of income where income is measured by $y - p_j$, then

(5-6) $$s_j = c_0 - c_1(y - p_j).$$

Substitution of (5-6) yields

$$\alpha_2 {s_j}^2 - \alpha_1 s_j - 2\alpha_2 s_j (y - p_j)$$
$$= \alpha_2[c_0 - c_1(y - p_j)]^2 - \alpha_1[c_0 - c_1(y - p_j)] - 2\alpha_2[c_0 - c_1(y - p_j)](y - p_j)$$
$$= \alpha_2 c_0^2 - 2\alpha_2 c_0 c_1 (y - p_j) + \alpha_2 c_1^2 (y - p_j)^2 - \alpha_1 c_0 + \alpha_1 c_1 (y - p_j)$$
$$- 2\alpha_2 c_0 (y - p_j) + 2\alpha_2 c_1 (y - p_j)^2$$
$$= \alpha_2 c_0^2 - \alpha_1 c_0 + [\alpha_1 c_1 - 2\alpha_2 c_0 (c_1 - 1)](y - p_j) + (\alpha_2 c_1^2 + 2\alpha_2 c_1)(y - p_j)^2.$$

This implies that the first three right-hand terms of the utility specification become

$$\alpha_0 + \alpha_1(y - \overline{p}_j) + \alpha_2(y - \overline{p}_j)^2 = \overline{\alpha}_0 + \overline{\alpha}_1(y - p_j) + \overline{\alpha}_2(y - p_j)^2$$

where

$$\overline{\alpha}_0 = \alpha_0 + \alpha_2 c_0^2 - \alpha_1 c_0$$
$$\overline{\alpha}_1 = \alpha_1 + \alpha_1 c_1 - 2\alpha_2 c_0 (c_1 - 1)$$
$$\overline{\alpha}_2 = \alpha_2 + \alpha_2 c_1^2 + 2\alpha_2 c_1.$$

Thus, under the assumption of (5-6), the presence of a nontrivial credit constraint is readily accommodated by the utility specification used in this chapter without further modification. However, this specification does not allow testing for the presence of a credit constraint because its role is implicitly represented in the utility specification. While other arbitrary specifications could be used in place of (5-6), some of which could permit testing for the presence of an effective credit constraint, this derivation shows that such tests would not be inconclusive because they would be dependent on an arbitrary specification. Thus, good estimates of the shadow value of credit are needed for reliable estimation and testing under constrained credit.

Chapter 6. Welfare Analysis and Policy Implications

Introduction

With the tight budgetary constraints that usually exist in Indian households, prioritizing public sector investments on the basis of expected benefits is essential. The purpose of this chapter is to explore the magnitude of the welfare impacts of different policy intervention scenarios based on the model estimated in the previous chapter and to provide policy recommendations. I first review the strategy for measuring welfare in discrete choice models, and then estimate welfare effects for leading policy scenarios. I then discuss policy implications with a focus on practical application and potential failures of improved stove programs and provide conclusions.

Measuring Welfare in Discrete Choice Models

The welfare effect of a change in the quality characteristics of one or more alternatives in discrete choice models can be measured by compensating variation (*CV*). Depending on the availability of information to the agent when compensation is paid, *CV* can be measured as ex post *CV* or ex ante *CV*. In the random indirect utility model $V(y - p_j, \mathbf{q_j}, \varepsilon_j)$ with income *y* where discrete choice *j* has price p_j and quality characteristic vector $\mathbf{q_j}$, and the random term ε_j associated with choice *j* is known to a household at the time of compensation, ex post *CV* is the amount of money that must be taken away from the household after the change in $\mathbf{q_j}$ to restore the utility level the household would have had without the change in $\mathbf{q_j}$. If the random term ε_j is not known to the household at the time of compensation, then ex ante *CV* is the appropriate welfare measure, which is the amount of money that must be taken away from the household given the change in $\mathbf{q_j}$ to restore the *expected* utility level the household would have had without the change in $\mathbf{q_j}$ (Just et al, 2004).

In the case of energy technology choices where a different random term is associated with each technology alternative, the random term associated with the technology used prior to the change may be known to the household by experience. However, the value of random terms associated with technology choices not previously selected may be unknown to the household. Furthermore, even though random terms may be known to the households, estimation of them by the researcher may be impossible without additional survey data that can identify them. Lack of information about the random term associated with either the initial or subsequent technology prevents calculation of ex post *CV* because the compensation required by each household depends on the household's random term for both initial and subsequent selected technologies.

Stated another way, revealed preference data permits estimation of agents' actions and thus preferences in response to information available at the time of choice, but such possibilities do not exist in the ex post context because no choices are observed once a household has incurred the fixed cost of a new technology, i.e., the technology choice cannot be corrected costlessly once a little experience is gained with a new technology. Hence, I regard ex post *CV* measurement as infeasible. Therefore, assuming households do not know both random terms a priori, I measure ex ante *CV* as

(6-1) $$v(y - p_j^0, \mathbf{q_j^0}) = v(y - CV - p_j^1, \mathbf{q_j^1})$$

where $v(y - p_j, \mathbf{q_j}) = E[V(y - p_j, \mathbf{q_j}, \varepsilon_j)]$ and superscripts 0 and 1 denote the initial and subsequent situations, respectively. I allow p_j to be changed to incorporate the scenarios that affect stove cost (e.g., a stove price subsidy) or fuel cost (which is affected by both stove efficiency and fuel price).

For this case where disturbances are identically and independently distributed with type I extreme value distributions, the log sum identity implies

$$\begin{aligned} E[V(y-p_j,\mathbf{q_j},\varepsilon_j) &= E[\max_{j\in J} V(y-p_j,\mathbf{q_j},\varepsilon_j)] \\ &= E[\max_{j\in J}\{v(y-p_j,\mathbf{q_j})+\varepsilon_j\}] \\ &= \ln\sum_{j=1}^{J}\exp\{(v(y-p_j,\mathbf{q_j})\}+C \end{aligned}$$

where C is a constant. As explained by Bockstael and McConnell (2007), C represents Euler's constant, although they make the argument that this measurement is only true up to an unknown constant because the absolute level of utility can never be measured.

Assuming that the current technology is the welfare maximizing technology in the initial situation and by substituting the log sum identity, equation (6-1) can be written as

(6-2) $$\ln\sum_{j=1}^{J}\exp\Big(v(y-p_j^0,\mathbf{q_j^0})\Big)=\ln\sum_{j=1}^{J}\exp\Big(v(y-CV-p_j^1,\mathbf{q_j^1})\Big)$$

because the C's cancel out. The CV defined by (6-2) is the ex ante compensating variation, which measures the amount of money taken from income that will yield the same expected utility of the preferred choice after the change in $\mathbf{q_j}$ and/or $\boldsymbol{p_j}$ as the expected utility of the preferred choice before the change. This equation does not yield an explicit solution in general, but can be solved numerically using estimates from Chapter 5.

Welfare Analysis of Policy Scenarios

Since IAP caused by burning biomass in traditional stoves is one of the top preventable health risks in India, the main objective of policy intervention is to mitigate the negative effects of traditional biomass use. A number of options are available, ranging from behavioral change to better kitchen ventilation and including use of more efficient stoves or the use of cleaner fuels. As analyzed in Chapter 5, large scale switching to clean fuels is unlikely to occur unless household income is substantially increased. Thus, I focus on policy intervention designed to promote improved stoves and improving kitchen ventilation rather than adoption of clean stoves. In addition, because LPG is currently highly subsidized in India and removal of the subsidy is under consideration, I consider a policy scenario where the government removes the LPG subsidy.

The term 'improved stove' is a general term that refers to a stove that has improved features compared to a traditional stove but still use traditional biomass. With this broad use of the term, improved stoves can have a wide range of performance measures and costs. The improved features mainly include efficiency, cleanliness, and convenience. All improved stoves are designed to improve fuel efficiency and some advanced improved stoves can save more than 50% of traditional fuel use compared to the traditional stove. If a chimney is included with an improved stove, IAP from traditional fuel combustion can be significantly reduced. Even if a chimney is not included, IAP from improved stoves can still be considerably less than from traditional stoves because less fuel is used. In addition, improved stoves can save cooking time due to improved stove efficiency.

As discussed in Chapter 2, although India initiated the National Program for Improved Chulhas (NPIC) in 1983, it was terminated due to a low continuing adoption rate. Only 5% of households used improved stoves in the survey. Because the number of households using improved stoves was so small, I did not include this stove option when estimating household behavior with respect to energy technology choices in Chapter 5. Further, recent reviews by Krishna (2007) and Barnes et al (forthcoming) have found that the poor stove design, low quality and durability, ineffective subsidy structure, and lack of after-sale service and maintenance are major contributors to the NPIC's failure. Thus, results based on inferior improved stoves may have been of little value for evaluating future policy alternatives.

Due to concerns that households would not pay higher prices for improved stoves, the NPIC focused on low cost improved stoves made from mud or cement with poor design and low quality. The cost of such an improved stove was about 180 to 200 Rupees and was designed to be only 20-30% more efficient than traditional stoves (Barnes et al, forthcoming). Many such improved stoves turned out to have low durability and were broken much earlier than the claimed two-year lifetime. The low durability was due to poor maintenance, stove modifications by users, and deterioration of the stoves themselves. This type of improved stove stands in sharp contrast to the improved stoves that have been promoted in Guatemala. Costs of these improved stoves ranged from $80-$110[9] and users of the improved stove reported a savings in firewood consumption of 50-67% (Energy Sector Management Assistance Program, 2004b). These improved stoves last at least four years and some good-quality stoves at the higher end of the cost range can last 10 years or more.

Subsidies on stove costs accounted for the largest share (50%) of government support of the NPIC. However, they were not effective. According to the policy of NPIC, a subsidy of up to one half of the stove cost was given as a direct discount to all national program beneficiaries. At the village level, user contributions varied widely across household categories. Households in backward classes received additional subsidies from some villages and paid little or nothing (Barnes et al, forthcoming). Table 6-1 gives an example of the cost and subsidy structure of improved stoves in the NPIC. Although subsidies encouraged households to purchase them, once the stoves were purchased, because no follow-up subsidies were offered for spare parts

[9] Some stoves were reported to cost as much as $154-$167 due to transport conditions.

and maintenance, many households chose not to continue to use them when some parts failed to work properly.

Table 6-1. Cost and Subsidy Structure of Improved Stoves in the NPIC

Cost in Rs (US$)	Fixed cement two-pot Laxmi with chimney	Fixed cement two-pot Parvati without chimney	Two-pot mud stove with chimney
Unit	200 (4.2)	180 (3.8)	180 (3.8)
Central subsidy	80 (1.7)	80 (1.7)	40 (0.8)
Labor cost covered by non-central subsidy	30 (0.6)	30 (0.6)	30 (0.6)
Beneficiary share	90 (1.9)	70 (1.5)	110 (2.3)

Sources: Barnes et al (forthcoming).

Barnes et al (forthcoming) find that households that benefited from the largest subsidies exhibited the poorest maintenance. Having paid nothing for an easily accessible product, these households did not appreciate its benefits. This shortcoming was compounded by the local administration's failure to conduct awareness-raising activities on the benefits of stove maintenance and how to perform it. Within six months, these poorly maintained stoves fell into disuse. Furthermore, the high percentage of subsidies on stove costs provided by the government has created market distortions that make it impossible for stove manufacturing companies to compete freely, which further caused the program to be financially unsustainable.

Since improved stoves can have many advantages over traditional stoves, especially on saving fuel and removing smoke, the policy makers in India may consider reviving the improved stove program. However, before redesign of the improved stove program, it is important to understand how much households are willing to pay for improved features included in improved stoves. This will help policy makers to understand whether households prefer high-cost, high-quality stoves or low-cost, low-quality stoves, and whether subsidies on stove costs are necessary for households to purchase improved stoves.

I consider three scenarios characterized by stylized hypothetical improved stoves:

Scenario 1. Introduction of advanced improved stoves that can reduce fuel cost by 50%, reduce IAP by 50%, and reduce cooking time by 12% (about 25 minutes). These characteristics are comparable to the designed performance of the improved stoves seen in Guatemala.

Scenario 2. Introduction of improved stoves that can reduce fuel cost by 25%, reduce IAP by 10%, and reduce cooking time by 3% (about 6 minutes). These characteristics are comparable to the designed performance of the improved stoves with chimneys in the NPIC.

Scenario 3. Introduction of efficiency-only improved stoves that can reduce fuel cost by 25% without reducing IAP and cooking time. These characteristics are comparable to the designed performance of the improved stoves without chimneys in the NPIC.

Because improved stoves were not included as an option in the estimated model of energy technology choice in Chapter 5, improved characteristics are applied to traditional stoves directly, which is equivalent to replacing traditional stoves with improved stoves. In other words, inefficient traditional stoves are not regarded as an option in these three policy scenarios. Therefore, welfare analysis for these three policy scenarios does not examine voluntary adoption of improved stoves in place of traditional stoves, but intends to evaluate welfare change or willingness to pay for improvement of certain attributes of traditional stoves as if use of improved stoves is imposed. These policy scenarios can also be considered as phasing out inefficient traditional stoves by imposing minimum energy efficiency requirements for stoves that use traditional biomass, in which case inefficient traditional stoves would no longer be an option. In this case, different stove attributes in the policy scenarios would represent the various requirements. In fact, some countries such as Brazil and Russia have established minimum energy efficiency requirements for cooking appliances (gas).[10]

The detailed changes in stove attributes associated with each scenario are shown in Tables 6-2, 6-3, and 6-4.

Table 6-2. Changes in Stove Attributes Under Scenario 1

Choice	Energy Technology	Monthly Cooking Cost (Rs/month)				IAP Mean Concen-trations (mg/m3)	Cooking Time (Hours)
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu		
1	One Improved Stove	113	68	63	107	0.28	3.08
4	Both Primary and Secondary Stoves are Improved	115	69	64	109	0.35	2.68
5	Primary Stove is Improved; Secondary Stove is Kerosene	217	168	257	242	0.28	2.67
6	Primary Stove is Improved; Secondary Stove is LPG	228	239	231	264	0.28	3.10
7	Primary Stove is Kerosene; Secondary Stove is Improved	485	424	798	603	0.22	2.72
8	Primary Stove is LPG; Secondary Stove is Improved	485	664	647	647	0.22	2.60

Improving kitchen ventilation can also reduce indoor air pollution. This can be accomplished by advocating behavioral change, such as open windows during cooking or more dramatic measures such as changing stove location, enlarging windows, adding a vent, or adjusting kitchen structures. The ventilation policy scenario considered here is:

Scenario 4. Adoption of a policy of advocating behavioral change to improve kitchen ventilation that achieves an IAP reduction of 20% for those households that have poor ventilation conditions. As discussed in Chapter 3 and shown in Table 3-3, compared to poor

[10] See the Collaborative Labeling and Appliance Standards Program as described at http://www.clasponline.org/clasp.online.worldwide.php?productinfo=52#Countries (website was accessed on July 6, 2009).

ventilation, moderate ventilation can reduce IAP by 15% and good ventilation can reduce IAP by 40%. This policy scenario chooses a 20% target assuming that poor ventilation conditions can be improved to moderate ventilation conditions through relatively simple behavior change. Table 6-5 shows IAP levels associated with various technology choices under this scenario.

Table 6-3. Changes in Stove Attributes Under Scenario 2

Choice	Energy Technology	Monthly Cooking Cost (Rs/month)				IAP Mean Concen-trations (mg/m3)	Cooking Time (Hours)
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu		
1	One Improved Stove	169	102	94	160	0.50	3.39
4	Both Primary and Secondary Stoves are Improved	171	103	95	162	0.63	2.99
5	Primary Stove is Improved; Secondary Stove is Kerosene	262	194	282	284	0.50	2.98
6	Primary Stove is Improved; Secondary Stove is LPG	273	266	256	307	0.50	3.41
7	Primary Stove is Kerosene; Secondary Stove is Improved	496	431	804	613	0.27	2.72
8	Primary Stove is LPG; Secondary Stove is Improved	497	671	653	658	0.27	2.60

Table 6-4. Changes in Stove Attributes Under Scenario 3

Choice	Energy Technology	Monthly Cooking Cost (Rs/month)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
1	One Improved Stove	169	102	94	160
4	Both Primary and Secondary Stoves are Improved	171	103	95	162
5	Primary Stove is Improved; Secondary Stove is Kerosene	262	194	282	284
6	Primary Stove is Improved; Secondary Stove is LPG	273	266	256	307
7	Primary Stove is Kerosene; Secondary Stove is Improved	496	431	804	613
8	Primary Stove is LPG; Secondary Stove is Improved	497	671	653	658

Table 6-5. Changes in Stove Attributes Under Scenario 4

Choice	Energy Technology	IAP Mean Concentrations (mg/m^3)
1	One Traditional Stove	0.45
2	One Kerosene Stove	0.17
3	One LPG Stove	0.17
4	Both Primary and Secondary Stoves are Traditional	0.56
5	Primary Stove is Traditional; Secondary Stove is Kerosene	0.44
6	Primary Stove is Traditional; Secondary Stove is LPG	0.44
7	Primary Stove is Kerosene; Secondary Stove is Traditional	0.22
8	Primary Stove is LPG; Secondary Stove is Traditional	0.22
9	Primary Stove is LPG; Secondary Stove is Kerosene	0.15

The Government of India has been spending billions of dollars each year subsidizing kerosene and LPG. For example, the government allocated an Rs 81 billion subsidy (approximately US$1.8 billion) for fiscal year 2003–04 (Energy Sector Management Assistant Program, 2003). The subsidized price in New Delhi as of February 2003 was Rs 241/cylinder while the unsubsidized price was Rs 469/cylinder. Due to a number of problems with the fuel subsidies, such as a fiscal deficit, market distortions, and supply constraints, government subsidies are expected to decline substantially in future years. Because this reduction has the potential effect of increasing IAP, I consider a final policy scenario to examine the magnitude of this impace. Because kerosene is also often used for lighting in rural India when electricity is not available or unreliable my model is able to capture the full welfare effect of eliminating the kerosene subsidy. Therefore, I consider:

Scenario 5. Phase out the subsidy on LPG by increasing LPG fuel price by 40%. The reason I consider 40% is that the LPG price in this data set ranges from Rs 270/cylinder to Rs 340/cylinder, suggesting that the subsidize level was not as high in many areas as in New Delhi. A major concern associated with phasing out the LPG subsidy is that households now using clean fuel may switch back to traditional fuels. However, as shown in Chapter 5, the LPG price increase causes the use of traditional fuels to increase only slightly. Table 6-6 shows how much cooking cost changes (in the cases where cooking cost changes) with various technology choices under this scenario.

Table 6-6. Changes in Stove Attributes Under Scenario 5

Choice	Energy Technology	Monthly Cooking Cost (Rs/month)			
		Uttarakhand	West Bengal	Madhya Pradesh	Tamil Nadu
3	One LPG Stove	771	1099	1072	1057
6	Primary Stove is Traditional; Secondary Stove is LPG	347	340	326	394
8	Primary Stove is LPG; Secondary Stove is Traditional	666	910	886	892
9	Primary Stove is LPG; Secondary Stove is Kerosene	746	995	1067	1004

Policy Implications

Welfare effects measured as expected compensating variation as defined in equation (6-2) are summarized in Table 6-7 by policy scenario.

Table 6-7. Average Household Welfare Effects by Policy Scenario

	Policy Scenarios				
Welfare Effects	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4***	**Scenario 5**
ECV	471	123	31	136	-44
Urban	348	84	23	109	-70
Rural	532	142	35	145	-31
Uttarakhand	514	135	37	106	-45
West Bengal	442	111	24	169	-54
Madhya Pradesh	439	112	24	168	-36
Tamil Nadu	490	132	38	109	-41

*Welfare effects are for those households who have poor ventilation conditions.

A. An Improved Stove Program Emphasizing Advanced Improved Stoves

Policy scenario 1 of replacing traditional stoves with the advanced improved stoves has the highest gains. The welfare gain for an average household to get such an improved stove is Rs 471 per month. Assuming that such an improved stove has a lifetime of five years and the annual discount rate is 12%, this means that an average household is willing to pay Rs 20,374 for such a stove (approximately $407), which is about four times the price of improved stoves seen in Guatemala.

Policy scenarios 2 and 3 are included to demonstrate how an advanced improved stove program can perform relative to the previous NPIC effort. Policy scenario 2 considers replacing traditional stoves with intermediate improved stoves of the type distributed by the NPIC with chimneys. In this case, households' willingness to pay declines sharply because stove performance is sharply lower. An average household is willing to pay only Rs 123 per month. Assuming such a stove has a lifetime of two years, this is equivalent to Rs 2495 per stove (approximately $50), which is more than ten times of the cost of improved stoves in the NPIC.

Policy scenario 3 considers replacing traditional stoves with efficiency-only improved stoves similar to the type distributed by the NPIC without chimneys. In this case, the willingness to pay declines further to Rs 31 per month or about Rs 629 per stove (approximately $13) because households only benefit from fuel savings. This amount is also well above the improved stove cost of the NPIC. Comparing scenarios 2 and 3 to scenario 1, the results show that in addition to fuel cost savings, households put considerable values on IAP reduction and cooking time savings, which explains how an advanced improved stove program can be successful even though the NPIC improved stove program failed.

Table 6-8 also shows that rural households benefit more from improved stoves compared to urban households. This is because traditional biomass is cheaper and more accessible in rural areas and, as a result, rural households are more likely to use traditional biomass. Thus, they benefit more from more efficient and cleaner stoves that still use traditional biomass. Among states, households in Uttarakhand and Tamil Nadu have a higher willingness to pay for improved stoves compared to the other two states. This is because traditional biomass is more expensive in these two states, which means households benefit more from improved stove efficiency.

The results from scenarios 1, 2, and 3 show that improved stoves can bring significant welfare improvements to households if they are designed with the attributes households value. However, the results of this welfare analysis must be interpreted with caution. First, this welfare analysis considers the hypothetical case where all traditional stoves are replaced by improved stoves. Voluntary adoption of improved stoves is not considered per se. Technically, the hypothetical case applies only if the government imposes a mandatory phase-out of inefficient traditional stoves. Second, the welfare analysis only considers benefits of improved stove efficiency, reduced indoor air pollution, and reduced cooking time from improved stoves, but does not consider adoption and maintenance costs of using improved stoves. Because stove design and materials are different than for traditional stoves, households must learn how to use improved stoves properly and may need to adjust their previous cooking practices. In addition, improved stoves must be maintained regularly to ensure their continued performance. Households need either to learn how to maintain the improved stoves by themselves or hire professionals to do it. If improved stoves are not used properly or are poorly maintained, the designed performance will not be achieved or the improved stoves may be broken, as happened with the NPIC.

Nevertheless, the welfare analysis shows that households would have significant welfare gains from improved features, even at much higher stove costs, if better features were incorporated into improved stoves compared to those distributed by the NPIC. Thus, willingness to pay should not be a major problem and subsidies do not appear to be required if households are ensured that the designed performance of improved stoves can be achieved, even for expensive advanced improved stoves.

Experiences with improved stove programs from several other countries also show that ensuring performance of improved stoves is the key for success. Guatemala was among the first countries in Latin America and the Caribbean to focus on improved stove design in the late 1970s (Ahmed et al, 2005). The early improved stove in Guatemala was built completely of mud. Although it worked well initially, its poor durability and, hence, reduced efficiency became evident with daily use. Eventually, it failed to significantly outperform traditional models. As a result, few people continued to use it. But by the mid-1990s, a more durable model was made available, which has a metal top for cooking, a shelf for feeding wood, space on top for placing cooking utensils and equipment, and a chimney for venting smoke. It remains popular today (Barnes et al, forthcoming).

China's improved stove program, like the NPIC, focused initially on rapid dissemination, accompanied by low-cost strategies and significant subsidies. Similar to the early Guatemalan experience, inexpensive construction resulted in poor performance and a low adoption rate. In subsequent program phases, the government played a smaller but more critical role. In the second phase, it reduced subsidies and pushed for commercialization of improved stoves. In the third phase, it shifted emphasis to extension, promotion, and increased standardization of the most popular models. These efforts were coordinated mainly through the Ministry of Agriculture's rural energy offices, which promoted various rural energy programs. Today more than 200 million people in China have an improved stove (Barnes et al, forthcoming).

Based on this welfare analysis and the past experience of the NPIC and the improved stove programs of other countries, the Indian government might consider a new improved stove program strategy. First, India may consider promoting advanced improved stoves instead of low-cost low-quality improved stoves because (1) households put considerable values on IAP reduction and cooking time savings while low-cost, low-quality improved stoves offer little improvement in these features; (2) the previous version of improved stoves already has a bad reputation due to its low durability; (2) the benefits from advanced improved stoves are more observable, so households can be more easily convinced; and (3) from a public health perspective, advanced improved stoves would be more beneficial as they can reduce most pollutants from traditional biomass burning.

Second, instead of subsidizing improved stove prices, government expenditures may be more effective if used to support the development of technical backup, impose quality control facilities, provide training related to stove design and maintenance and health knowledge, and monitor and evaluate program progress by collecting feedback from users. This would help to integrate the design, construction, delivery, and maintenance service as required for overall program success.

Third, the government should support the process of commercialization of high-quality improved stoves. This can be done through the formulation of policies to provide incentives to private sector operators to produce, distribute, and sell improved stoves. Government assistance can also take the form of providing technical standards (such as setting minimum energy efficiency requirements), facilitating the availability of raw materials, establishing credit for stove makers, and offering promotional support. Providing a good investment and regulatory environment will also help stove producers to scale up production and lower the stove costs.

B. Promotion of Improved Ventilation

Policy scenario 4 considers reducing IAP for those households with poor ventilation conditions through advocating behavioral change. The estimated welfare gain for the average household with poor ventilation is Rs 136 per month. As 75% of households with poor ventilation conditions are in rural area, such a policy will particularly benefit rural households. West Bengal and Madhya Pradesh have a relatively higher share of households with poor ventilations. Thus, targeting these areas will be more effective, suggesting these areas might be good choices for pilot projects. More particularly, provincial and local governments can identify areas that have a high share of households with poor ventilation and then consider organizing an advocacy campaign to educate households about how to improve kitchen ventilation through behavioral change and other relatively simple measures. Depending on the efficiency of such efforts, this type of policy may have the potential of producing significant welfare gains for targeted households at low cost.

C. The Welfare Impact of Discontinuing the LPG Subsidy

Policy scenario 5 considers the effect of increasing LPG fuel price by 40%, which is intended to reflect the magnitude of effective LPG prices to households with a discontinuation of the LPG subsidy. The estimated welfare loss for an average household is Rs 44 per month. Urban households would have a higher average welfare loss of Rs 70 per month because clean stoves are more prevalent among urban households. In contrast, rural households would only have an average welfare loss of Rs 31 per month. This is slightly less than the extra LPG fuel bill of Rs 43 per month the average rural household needs to pay if the LPG subsidy is lifted and the energy technology choice does not change. The reason the LPG price subsidy turns out to be largely a simple transfer to households with little welfare gain is that the impact of the

LPG price increase on household energy technology choice is small. Only about 0.1%-3.1% of rural households would switch their primary stove from a clean stove to a traditional stove as a result of the LPG price increase, whereas fuel use is quite inelastic once a given stove technology is in place. From the perspective of social welfare, if the government phases out the subsidy on LPG prices, the effect is negligible. This is one reason that an alternative use of government funds to establish infrastructure for advanced improved stoves or for advocacy regarding ventilation promises more significant welfare improvements.

Conclusions

In this chapter, based on the household behavioral model of energy technology choice estimated in Chapter 5, I have examined the welfare impacts of different policy scenarios that might impact household IAP levels. The policy interventions focus on the policies that can change energy technology attributes to mitigate the negative impacts of traditional biomass fuels as well as the policies that phase out high clean fuel subsidies or directly encourage clean stoves. The results clearly show that households' willingness to pay for improved stoves that can save biomass fuels, reduce IAP, and save cooking time is high and well above the price of advanced improved stoves that offer superior performance. Rural households have even higher willingness to pay for such a stove. In addition, households' welfare gain from improvement in indoor air quality, such as may be possible with advocacy programs, also appears to be high. Phasing out subsidies on LPG fuel prices, on the other hand, causes negligible welfare loss for an average household because it has little impact on household energy technology choices. Given that traditional biomass will continue to be the most popular cooking fuel in the near future, the welfare analysis strongly supports the policy of promoting advanced improved stoves.

However, to make an improved stove program successful, it has to be well designed and implemented. The high willingness to pay in the welfare analysis depends on convincing households that improved stoves will achieve the designed performance and assumes that adoption and maintenance costs not captured by the model will not be significant. Thus, the key for success appears to be ensuring the quality and durability of improved stoves to earn households' trust. Although no subsidies on stoves are needed, support should be given to developing technical backup units, setting up improved stove standards and quality control facilities, and providing training regarding stove design and maintenance and health knowledge. The improved stove program should also support the commercialization of improved stoves through providing incentives to private sector operators to produce, distribute, and sell improved stoves.

Due to model limitations, I considered only policy interventions that affect energy technology attributes and do not quantify the welfare impacts from policy interventions that alter household characteristics such as household income, health knowledge, and women's wage rates. However, the model implies that increased household income, improved health knowledge, and increased women's opportunity cost of time (through improved wage rates) should increase households' adoption of cleaner energy technologies. Therefore, the improved stove program combined with an indoor air pollution campaign and training for women is likely to bring more welfare to households.

Chapter 7. Conclusions

About half of the world's population, over 3 billion people, still rely on traditional biomass fuel such as wood, dung, and crop residue for domestic energy needs (Bruce, et al., 2002). Indoor air pollution (IAP) caused by burning traditional biomass fuel has been a major environmental and public health hazard for these people. However, the transition to cleaner fuels among the poor has been slow. Further, evidence shows that reliance on biomass is increasing in some parts of the world (Bruce, et al., 2002).

Why do people use household energy technologies that can make them sick or even cause death? This dissertation has developed a unified framework to explore this puzzle by quantifying the relationships among household energy use, indoor air pollution, and health impacts that can enable policy-makers to analyze welfare gains from different policy interventions. With the tight budgetary constraints that usually exist, it is important to be able to prioritize public sector investments on the basis of expected benefits.

Summary of Conclusions and Contributions

Using a uniquely rich household survey data set from India, this dissertation has developed a unified framework including four interlinked modules that answer the following research questions, respectively.

Which factors determine IAP concentration and what are their relative contributions?

Analysis of the first module shows that having a clean stove such as an LPG or kerosene stove as the primary stove significantly reduces PM 2.5 concentrations in kitchens. For example, if an average household switches from using both a traditional primary stove and a traditional secondary stove to only using one clean stove, the PM 2.5 mean concentration will decline by 0.543 mg/m^3 or 71%. Having a clean stove as the secondary stove is not statistically significant in reducing PM 2.5 concentrations. This implies that partial fuel switching may not have significant impacts on household IAP levels. If households use clean fuels only occasionally (such as for making tea) and still use traditional biomass for primary cooking, the household IAP level does not change much.

Having an improved stove that burns traditional fuel can potentially reduce PM 2.5 concentrations considerably as well. But due to the small number of households using an improved stove, statistical significance for this effect could not be found. In addition, ventilation conditions play a significant role in IAP concentrations. If an average household can improve ventilation conditions from poor to good, the PM 2.5 mean concentration is reduced by 40%. Ventilation conditions can relate to a number of factors such as kitchen location, housing structure, and cooking practice.

Results further indicate that the amount of fuel use does not have significance in determining PM 2.5 concentrations when fuel types and other factors are controlled. This result likely occurs because starting the fire is the most polluting part of the cooking process. Since measuring fuel quantity is costly and time-consuming, this is an important finding that can contribute to future study designs.

The analysis of the first module also demonstrates how an IAP index can be constructed to predict typical households IAP exposure levels. Directly measuring IAP concentrations using personal or area monitors can be quite costly and hard to apply to a large sample. In addition, IAP concentrations are typically monitored only for short time intervals, which introduces noise that does not represent typical IAP exposure. This dissertation demonstrates how to develop an IAP index that can be used to predict typical IAP exposure levels. This is an important contribution to the literature that can be useful for the design of future studies by reducing cost and improving evaluation of health impacts and intervention programs.

What is the quantitative relationship between exposure to IAP and the related health impacts?

In the second module, both subjective self-reported respiratory symptoms and objective doctor-measured spriometric indicators are considered as health impacts of IAP. The analysis finds that an increase of 1 mg/m^3 in the PM 2.5 mean in the kitchen is associated with an 11.9 percentage point increase in the probability of reporting a respiratory symptom for those who are typically in the kitchen. This effect is about half of the effect of smoking, which underscores IAP as a major health concern.

Using FEV1, FVC, and FEV1/FVC as spirometric indicators, the analysis finds that an increase of 1 mg/m^3 in the PM 2.5 mean can reduce FEV1 of a person who is typically in the kitchen by 0.284 liters and reduce FVC by 0.254 liters. This effect is more than double of the effect of smoking. This implies that IAP is particularly harmful to spirometric function compared to general respiratory diseases. Nevertheless, the results do not show that the IAP exposure has a statistically significant impact on FEV1/FVC. Because obstructive lung disease decreases FEV1 and with a negligible effect on FVC, while restrictive lung disease decreases both FVC and FEV1 with a negligible effect on FEV1/FVC, the results imply that IAP has major impacts on restrictive lung disease rather than obstructive lung disease. The results thus provide an explanation for why the literature contains more evidence of IAP's impact on certain respiratory diseases such as ALRI for children but less or inconsistent evidence of IAP's impacts on other respiratory diseases such as asthma (a typical obstructive lung disease).

In addition, the results show that the health effects of using the PM 2.5 95th percentile as the IAP intensity indicator are much smaller than using the PM 2.5 mean as the indicator, amounting to less than 1/5 of the latter**.** This pattern is true for both using respiratory symptoms and spirometric indicators as the health outcome. Since the PM 2.5 95^{th} percentile represents a short-period high pollution intensity level while the PM 2.5 mean represents the 24-hour average pollution intensity, this result implies that daily average pollution intensity has more impact on respiratory health than maximum exposure.

By comparing the goodness of fit of regressions on spirometric indicators and on the respiratory symptoms, this second module shows that spirometry measurement is much more accurate in characterizing the effects of IAP while symptoms are more a random effect that causes noise in measurement.

In summary, the analysis of the second module makes several important contributions to the literature. First, in terms of exposure indicators, it uses a new exposure indicator—typical IAP exposure predicted from a direct IAP measure—which is better than using indirect measures such as fuel or stove types as proxies and better than using short-interval direct measures that include statistical noise. Second, in terms of the health outcome, this study uses both subjective self-reported respiratory symptoms and objective doctor-measured spirometric indicators to provide a more complete and consistent story. It also demonstrates that spirometry measurement is much more accurate than symptoms in characterizing the effects of IAP. Third, in terms of findings, it not only provides additional evidence on health impacts of IAP exposure compared to previous literature, but also adds new findings to the literature. In particular, while most previous studies focus on incidence of different symptoms and diseases as health outcome, this study analyzes spirometric function. It thus provides fundamental evidence about how IAP affects health, and is able to explain why certain diseases are more associated with IAP exposure. In addition, it provides quantitative results on how different IAP exposure intensity affects health.

What factors affect decisions on the energy technology choice?

The third module is a novel approach to modeling household behavior regarding the energy technology choice. Households are assumed to choose a cooking energy technology based on its attributes: cooking cost, convenience, and cleanliness. These attributes do not vary among households, but household valuation of these attributes depends on household characteristics. Results show that the marginal utility of income decreases as income increases and that this effect carries over into the cooking technology choice. Thus, households are less sensitive to cooking cost as income increases. This is an important explanation for why dirty technologies remain dominant among poor households. In fact, choices regarding clean technologies are more sensitive to income levels than to clean stove costs. Rural households barely change their energy technology choices if the LPG stove is reduced by 50%. But if income is doubled, 14%-24% of rural households switch their primary stove from a traditional stove to a clean stove depending on their residence. This analysis confirms that fuel switching on a large scale will not occur in rural areas unless rural economies become substantially more developed.

Results also show that women's opportunity cost of time affects household's valuation of the convenience of cooking energy technologies. Households are more likely to choose energy technologies with shorter cooking time in areas with higher wage rates for unskilled women, although this effect is not statistically significant. With respect to cleanliness, results show that households that know IAP is harmful to health are more likely to choose energy technologies with lower pollution levels.

In summary, the third module presents a new modeling approach regarding how to model household choice of cooking energy and technology. It shows that in addition to cost considerations, households also value convenience and cleanliness, although how much they value these attributes depends on their own characteristics such as opportunity cost of time and health awareness. By quantifying these factors, the estimation results from the third module enable a welfare analysis of various policy interventions.

What are the welfare effects of various interventions that affect the energy technology choice?

The fourth module focuses on identifying the welfare effects of policy intervention based on estimation results from the third module. The policy intervention scenarios focus on policies that can change energy technology attributes to mitigate the negative impacts of traditional biomass fuels as well as the policy of phasing out high subsidies currently offered on LPG fuel price. The results clearly demonstrate that households' willingness to pay for improved stoves that can save biomass fuels, reduce IAP, and save cooking time are high. The estimated welfare benefits are well above the price of improved stoves on the market given their claimed performance. For example, for an advanced improved stove that can reduce fuel cost by 50%, reduce IAP concentrations by 50%, and save cooking time by 12%, the results show that an average household is willing to pay Rs 471 per month, which generates a discounted benefit of Rs 20,374 per stove using a 12% annual discount rate and 5-year stove lifetime. This is about four times of the price of the advanced improved stoves that have been introduced in Guatemala. Rural households have even higher willingness to pay for such a stove.

However, the high willingness to pay in the welfare analysis assumes that households are convinced that improved stoves will achieve the designed performance and that adoption and maintenance costs not captured by the model will not be significant. If improved stoves are not used properly or poorly maintained, the designed performance will not be achieved and breakage can occur more quickly. In this case, based on the NPIC experience, households would not be interested in using an improved stove even if the stove cost is low. Thus, the key for success for an advanced improved stove program is to ensure the quality and durability of improved stoves to earn households' trust. Instead of subsidizing stove cost, the improved stove program should support the infrastructure required for integration of the design, construction, delivery, and maintenance service to stove users by developing stove performance standards, setting up quality control, developing technical backup, and providing training on stove benefits, usage, and maintenance. To be sustainable, the improved stove program should support the process of commercialization of improved stoves through incentives to private sector operators to produce, distribute, and sell improved stoves of proper quality.

In addition, households' welfare gain from improvement in kitchen ventilation also appears to be high. If a policy can improve a household's ventilation condition from poor to moderate, the average welfare gain for such a household is Rs 136 per month. Phasing out subsidies on LPG fuel price, on the other hand, generates a modest welfare loss for an average household and will have little impact on household energy technology choices. Given that traditional biomass will continue to be the most popular cooking fuel in the near future, the welfare analysis strongly supports the policy of promoting improved stoves if a new strategy is developed building on lessens from the past failure of the NPIC.

In summary, this dissertation is the first comprehensive study that presents a unified framework linking household behavior with the actual IAP levels it generates and the consequent health impacts sufficiently to enable welfare analysis of alternative policies. It provides quantitative evidence that IAP has significant health impacts comparable to smoking. Considering that traditional biomass will likely continue to be the most popular cooking fuel in rural areas in the near future, and that households can achieve considerable welfare gains from improvement in stoves and kitchen ventilation, the analysis suggests that the Indian government should consider reviving the improved stove program with a new advanced stove strategy and conducting advocacy campaigns on how to improve kitchen ventilations. The analysis suggests little overall welfare effects of the pending phasing out of LPG subsidies.

Future Research

The results of this dissertation are based on several assumptions that can be relaxed in future research when more information is available. First, the household behavioral model in the third module assumes initially that households do not have credit constraints that restrict upfront fixed costs of acquiring new cooking technology. However, this assumption may not hold in some areas in India where households do not use clean stoves because the upfront stove cost is high relative to income, and loans are not typically available for consumer items. In areas where credit constraints are a major barrier, the upfront stove cost may have a relatively higher effect compared to the monthly fuel cost due to the shadow value of credit. In such cases, policies such as promoting microfinance can help households adopt cleaner energy technologies. I show in the Appendix to Chapter 5 that this shadow value of credit can be accommodated in the model. If more information becomes available on how the shadow value of credit is determined, the assumption of no credit constraints can be relaxed accordingly. This will allow estimation and testing of how the credit constraints affect household behavior with respect to energy technology choices for cooking. Also, additional welfare analysis can be conducted on the welfare gains of promoting microfinance.

Second, lack of available data on voluntary choice of improved stoves constrains the welfare analysis on improved stoves to consider the hypothetical case that the government causes traditional stoves to be replaced by instituting regulations, for example, by a mandatory phase-out of inefficient traditional stoves. With more data in which a sufficient share of households use improved stoves, the estimates of the household behavior models as well as the welfare analysis on improved stoves can be improved. In addition, the welfare analysis does not consider adoption and maintenance costs of using improved stoves. The household adoption cost may be high if the cooking practice on the improved stoves is very different from on traditional stoves. Information is needed on households' usage of improved stoves such as how improved stoves affect household cooking practices and how often the stove needs to be maintained at what cost. These should be areas of emphasis in future data gathering efforts to support more robust welfare analysis.

Third, in the household behavior model, I use a form that models the utility of income available for expenditure on other goods, which implicitly assumes that cooking services are separable from all other goods in utility. However, because IAP can have a significant negative impact on health, cooking and related technology choices could potentially have an effect on health expenses. Based on the current model and the results, if information on health expense is available, it can be included in the model explicitly and linked to IAP exposure levels and health knowledge to make the framework more comprehensive. Additional welfare analysis can also be conducted to determine the welfare gains from improving health knowledge. Similarly, the opportunity cost of time can also be modeled explicitly so that welfare analysis can be conducted on policy intervention that increases women's opportunity cost of time by improving women's employment opportunities. Then the combined welfare gains can be measured for a policy that not only promotes improved stoves, but also provides health education and job training for women. Such a program, if implemented well, is expected to bring significant welfare gains to households.

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