Indoor air pollution in developing countries: Household use of traditional biomass fuels and the impact on mortality*

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Abstract

An estimated 2.5 to 3 billion people worldwide rely on biomass fuels to meet their household energy needs. Burning wood, animal dung, or crop wastes in simple stoves, these households typically generate high levels of indoor air pollution that adversely affect health, especially of women and young children.

Using cross-country data and household data from Pakistan, this thesis estimates the effect of biomass fuel use on infant mortality and child mortality. The simple cross-country results show positive, significant associations between biomass fuel use and infant and child mortality. Perhaps because of considerable strain on the data, these associations do not stand up to a configuration using a cross-country panel with country-specific fixed effects. On the other hand, household-level micro results show positive effects of traditional biomass fuel use on mortality, although the coefficients are not always well-determined.

Taken as a whole, the results support the conclusion that dependence on traditional biomass fuels leads to higher risks of child mortality. The estimates imply that a 10 percentage-point decrease in the share of energy consumption due to biomass fuels for a country lowers its child mortality rate by roughly 7 deaths per 1,000 live births. For a country such as Kenya, in which roughly three-fourths of total energy consumption is supplied by biomass fuels, the implication is that switching completely to non-biomass fuels would, *ceteris paribus*, lower its child mortality rate by 38 percent and prevent 54,000 deaths to children before the age of five. On a global level, the health effects associated with traditional biomass fuels potentially rival those of the HIV/AIDS epidemic.

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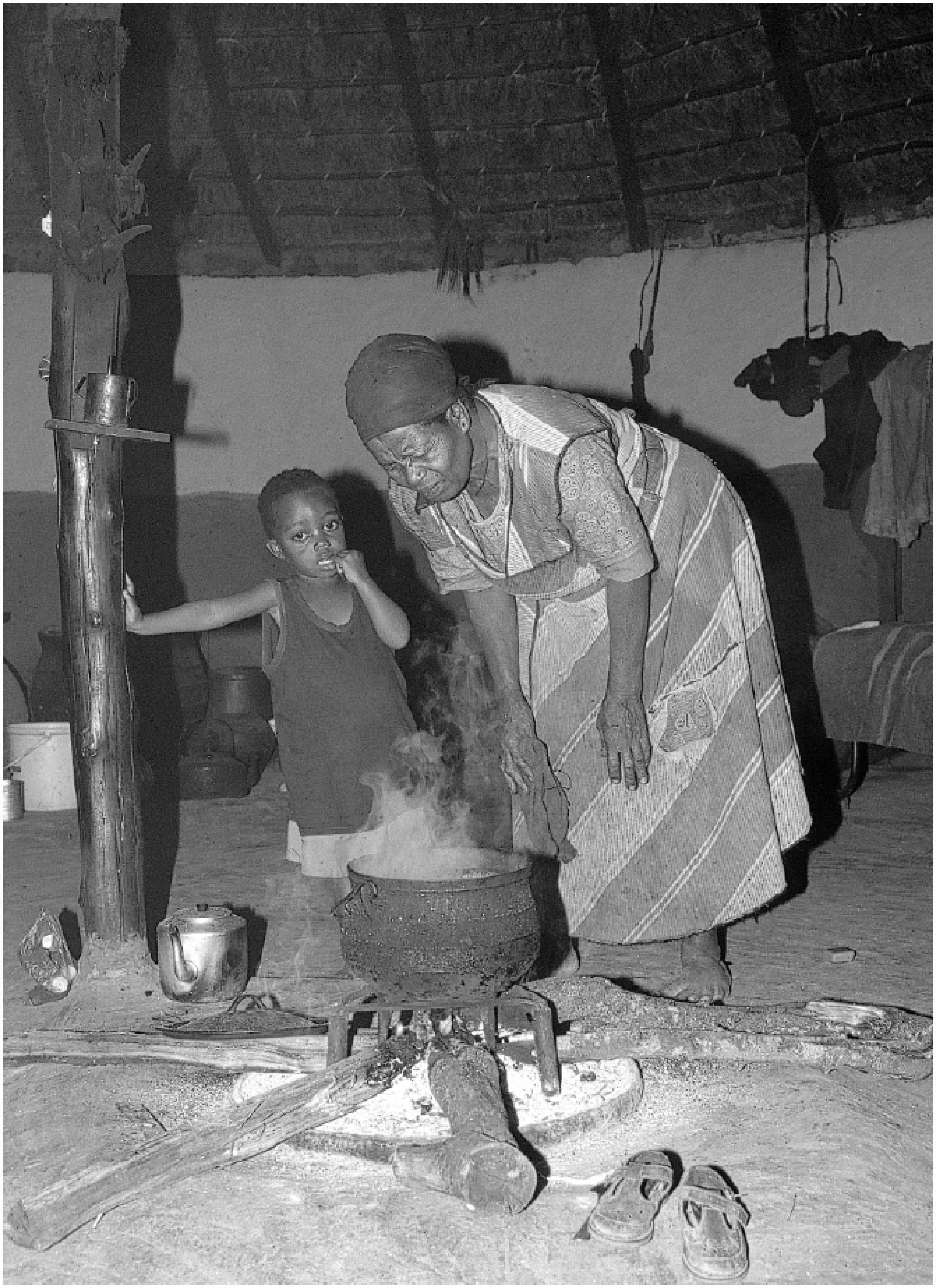
A simple wood stove in a traditional home in KwaZula, Natal, South Africa.



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1 Introduction

1.1 Energy, Poverty, and Household Fuel Decisions

Energy is essential to human survival, sustaining basic human needs such as temperature regulation, cooked food, and lighting. In the modern cities of today, sources of energy range from gas to electric to solar power, but in much of the world, the majority of people still lack access to clean, safe fuels. In fact, today an estimated 2.5 to 3 billion people and up to 90% of rural households in developing countries rely on biomass fuels in traditional ways for household energy needs (World Resources Institute, UNEP, UNDP, and World Bank 1998). While the share of global energy from biomass fuels has declined with the spread of modern fuels from 50 percent in 1900 to approximately 13 percent in 2000, recent trends suggest that the usage of traditional biomass fuels may actually be increasing among the poor in developing countries (World Health Organization 2002).

Figure 1 shows that the proportional use of traditional biomass fuels, which refer to wood, charcoal, animal dung, and crop wastes, is high in Asia, Latin America, and especially sub-Saharan Africa, where in many countries over 75 percent of energy consumed is generated from traditional biomass fuels. These countries also have high levels of poverty, suggesting a correlation between poverty and energy. Reddy (2001) suggests that an energy-poverty nexus exists where dependence on traditional biomass fuels is both a cause and result of poverty—lack of adequate energy can constrain development, while at the same time, poverty prevents the affordability and access to modern fuels.

This energy-poverty nexus also exists at the individual and household level, where the poor use a different set of energy carriers—they use disproportionately more traditional biomass fuels than the rich (Reddy 2001).[2] The different energy carriers that can be used to fuel household activities form what is commonly referred to as an "energy ladder," where each rung corresponds to the dominant fuel used by a particular income group (Reddy and Reddy 1994). Higher level income groups tend to use fuels at higher rungs. Wood, animal dung, and crop wastes represent the lowest rung on the energy ladder, with charcoal and coal, kerosene, liquefied petroleum gas (LPG), and electricity representing successive rungs up the ladder. The energy ladder also relates the efficiency and cleanliness of each fuel. Proceeding up the ladder, the fuels on each rung become more efficient in their end-use device and produce less emissions (not taking CO_2 into account). For example, Bloom et al. (1996) write that the cook-stove efficiencies of fuelwood, kerosene, and gas are approximately 15, 50, and 65 percent, respectively.

Empirical work by Reddy and Reddy (1994) on households in Bangalore suggests that an energy ladder does exist in practice. Their work shows that costs are the dominant factor in fuel-choice decisions and that the poor apply higher discount rates when making these decisions.[3] As a result of these two factors, the poor often use inefficient fuels at the bottom of the energy ladder, even when other fuels are available and are cheaper in the long-run, because they cannot afford the up-front costs for efficient devices or fuels. The available income of a household is therefore the main constraint on fuel-choice decisions in poor households. With higher incomes and access to alternative fuels, people tend to switch to more modern stoves and cleaner fuels, regardless of cultural traditions (Reddy et al. 1997).

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[2] An energy carrier is some means of moving energy from one location to another.

[3] The authors maintain, however, that households are not indifferent to non-cost aspects, particularly because it is difficult to separate out their effects. For example, fuels at higher energy rungs are generally cheaper, more convenient, and also cleaner. Analyzing the costs of a particular fuel also captures these non-cost aspects.

Since the poor often pay more for energy, the usage of traditional biomass fuels further exacerbates poverty. Poverty conditions are also worsened through the health and quality of life impacts associated with traditional biomass fuels. Direct effects include burns to children falling into fires, household fires, and respiratory illnesses from indoor air pollution. Indirect effects include the opportunity cost of time spent by women and children in collecting fuel, injuries from carrying large amounts of wood, restrictions on economic and educational activity due to poor air quality or lighting, environmental degradation due to increased resource stress from fuelwood collection, and the vulnerability of women to violence when collecting fuel in areas of civil unrest and war (Schirnding et al. 2002).[4]

1.2 Indoor Air Pollution and Health

Much research is still needed on the various health and quality of life impacts associated with traditional biomass fuels, but in the past decade, significant research has demonstrated that a primary pathway through which traditional biomass fuel use affects health is through indoor air pollution. Biomass fuels generally contain few contaminants such as sulfur or metals, so their complete combustion, under proper conditions, can result in "clean" products of carbon dioxide and water. Unfortunately, simple household stoves often do not allow enough airflow into and through the stove, limiting the amount of oxygen available for combustion. The problem with adequate airflow is also compounded because a trade-off exists between higher fuel efficiency and combustion efficiency—fuel efficiency is improved by narrowing the gap between the cooking vessel and the stove, but narrowing the gap further restricts airflow (Reddy et al. 1997).[5]

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[4] Dependence on wood for energy was originally thought to also contribute to deforestation and land erosion, but recent evidence has now shown that most fuelwood is collected and not cut, and that deforested areas do not coincide with fuelwood collection areas (Filmer and Pritchett 2002). In fact, fuelwood scarcity is generally the result of deforestation. However, fuelwood demand still contributes to greater environmental stress, and in localized cases such as in Sub-Saharan Africa, does contribute to forest depletion (Holdren and Smith 2001; Schirnding et al. 2002).

[5] Improved biomass stoves can improve combustion efficiency and reduce smoke emissions, but improved stoves programs have had mixed success in encouraging their usage (Schirnding et al. 2002).

Inefficient combustion results in a complex and unstable mixture of particulate matter, carbon monoxide, hydrocarbons, nitrogen oxides, formaldehyde, and benzene that often greatly exceed the standards for indoor air pollutants in developed countries such as those set by the U.S. Environmental Protection Agency (USEPA) (Schirnding et al. 2002). Table 1 provides a comparison of the levels of carbon monoxide and particulates less than 10 microns (PM10) recorded in indoor air pollution studies alongside WHO and USEPA air quality guidelines for those pollutants. Case studies in Asia, Africa, and the Americas have found particulate levels ranging from 300 to over 30,000 $\mu g/m^3$ during stove use, several times the USEPA 24-hour standard for PM10.

Actual human exposure to indoor air pollution depends on a variety of factors including household energy technology such as the existence of a chimney and the fuel-stove combination, housing characteristics such as the number of rooms and ventilation, and behavioral determinants such as the amount of time spent inside the house (Ezzati et al. 2000). Cooking often exposes individuals to high-intensity pollution episodes, occurring when fuel is added or moved, the stove is lit, the cooking pot is moved, or food is stirred (Ezzati and Kammen 2002a).

While few studies have measured human exposure directly, general evidence suggests that the populations most likely to be exposed to these high levels of indoor air pollution are women, because of their greater time spent cooking and indoors, and infants and young children, who often remain near cooking areas with their mothers (Schirnding et al. 2002). As a result, these populations are particularly at risk for a variety of adverse health effects related to indoor air pollution. Middle ear infection, tuberculosis, perinatal mortality (still births and death in the first week of life), low birth weight, eye irritation, cataract, asthma, and oral cancer have all been associated with biomass smoke in epidemiological studies. So far though, substantial and consistent evidence of a causal relationship exists only between indoor air pollution and acute respiratory illness (ARI), chronic bronchitis, and chronic obstructive pulmonary disease (COPD) (Bruce et al. 2000; Smith et al. 2000; Schirnding et al. 2002).[6]

An extensive review of the epidemiological literature by Smith et al. (2000) suggests that indoor air pollution significantly increases the risk of acute lower respiratory infection (ALRI), which is the most common cause of illness and death in children under 5 years of age.[7] With narrower respiratory passages and poorly developed immune systems, young children are particularly susceptible to indoor smoke that can impair clearing mechanisms of the respiratory tract and allow bacteria and viruses to enter the lower airways (Bloom and Zaidi 2002).

Infant and child deaths are therefore substantial health impacts attributable to indoor air pollution. In fact, Smith and Mehta (2000) estimate 1.8 million annual deaths result from global exposure to indoor air pollution, with approximately one million due to ALRI in children under 5 years. Because child mortality is such a substantial proportion of the deaths, the global burden of disease attributed to indoor air pollution is extremely high with 53 million disability-adjusted life years (DALYs) lost annually (Smith and Mehta 2000).[8]

2 Methodological Approach

In order to understand the broad effects of using biomass fuels in traditional ways, this thesis focuses on the effect of indoor air pollution on infant and child mortality. Epidemiological studies on indoor air pollution generally focus on morbidity. Indeed to date, only one

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[6] Limited epidemiological research on indoor air pollution in developing countries prevents one from concluding that a definite association exists between indoor air pollution and the health risks listed. Moreover, many studies suffer from lack of exposure determination and inadequate controls for confounding factors.

[7] ALRI, which includes bronchitis, pneumonia, and broncho-pneumonia is generally more severe than acute upper respiratory infection (AURI), which includes infections of the larynx, pharynx, tonsilar glands, eustachian tube, nasal cavities, and sinuses (Ezzati and Kammen 2002a). ALRI accounts for an estimated 3 to 5 million annual deaths worldwide (Smith et al. 2000)

[8] Burden of disease refers to the loss of health and premature mortality at the population level. Disability-adjusted life years (DALYs) are calculated as the number of years lost due to premature mortality plus the number of years lived with disability due to a disease with appropriate disability weights (Murray and Lopez 1996).

epidemiological study has found an association between indoor air pollution and mortality. Smith et al. (2000) writes that the case-control study in Nigeria showed that children with ALRI who came from homes that burnt wood were 12.2 times more likely to die than those from homes that burnt kerosene or gas.

Bloom and Zaidi (2002) conduct the only economic study to date on the health effects of indoor air pollution.[9] Regressing income and percent biomass fuel use on a wide range of demographic indicators, they find that biomass fuel use is positively and significantly associated with infant mortality, child mortality, crude birth rate, total fertility rate, and population growth rate. In particular, they show that a 10 percentage-point reduction in biomass fuel use would decrease the child mortality rate by 4.9 deaths per 1,000 live births.

In addition, Bloom and Zaidi (2002) find that the effect of biomass fuel use on the crude death rate is smaller in magnitude and significance than on infant and child mortality, which they argue reflects the disproportionate health effect of indoor air pollution on children. Their regressions also show a negative association between biomass fuel use and the life expectancy gap, reflecting greater health consequences with biomass fuel use for women than men. The authors suggest that this gender differential may be the result of greater female exposure to smoke emissions because of the more time they spend indoors.

This thesis will examine the robustness of their results using more recent cross-sectional data and panel data from 1971 to 2000. More importantly, this analysis builds on economic literature to specify appropriate models and configurations to account for omitted variables and improper specifications that likely bias the estimates by Bloom and Zaidi (2002).[10]

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[9] Bloom et al. (2000) also present the same regressions but with less discussion.
[10] Bloom and Zaidi (2002) conduct regressions for different dependent variables with the same functional form.

An analysis of cross-country data would be useful because levels of biomass fuel use across countries are likely to have greater variation, providing a potentially more statistically significant result. The greater variation also allows us to examine the potential health benefit of switching from a high biomass fuel use regime to a low biomass fuel use regime, controlling for income, health measures, and socioeconomic factors. With panel data, we can control for country-specific effects and provide a comparison for the cross-sectional results. The variation of biomass fuel use within countries is likely to be much smaller, however, as the greatest variation would be expected in developed countries that switched primarily to modern fuels before 1971.

Unfortunately, macro data may be less precise because of aggregation over households. Thus, the macro results are corroborated with micro data, which may be more reliable. At the same time, micro data may have substantial random noise, making it difficult to estimate the effect of traditional biomass fuel use amongst various other determinants of mortality. The macro and micro data therefore complement each other and provide a more comprehensive analysis of the mortality effect of traditional biomass fuel use.

2.1 Exposure and Biomass Fuel Use

The ideal data set for both analyses would be the actual exposure levels of individuals, but very few studies have conducted personal monitoring of exposures (Schirnding et al. 2002). In addition, these few exposure studies generally aggregate exposure over time and space, which limits the available information because combustion of traditional biomass fuels results in high-intensity emission episodes near the source. The next-best data set would be the amount of traditional biomass fuel burned in simple stoves in each household, including information on the type of stove, existence of a chimney, ventilation, housing structure and characteristics, and behavioral patterns. Fortunately, this type of micro data does exist for certain countries, although of different levels of comprehensiveness. In particular, the Pakistan Integrated Household Survey (PIHS) of the World Bank's Living Standards Measurement Study (LSMS) has the most extensive information on traditional biomass use including stove type, existence of a chimney, and where cooking occurs. Conducted in 1991, the survey contains detailed information that can account for a variety of confounding factors. The micro section will therefore examine the relationship between traditional biomass fuel use and infant and child mortality using the PIHS data set.

This type of household data from many countries can be aggregated for a macro analysis. Limited by the differences in questions regarding traditional biomass fuel usage among surveys of different countries, the best possible data are the percent of total population using traditional biomass fuel in each country. These global household fuel use data have actually been compiled by Smith et al. (2001) for their calculations of the global burden of disease from indoor air pollution. Data are only available for 52 countries, so Smith et al. predicts household traditional biomass fuel use for all other countries in the world using linear regression with a variety of development indicators including economic growth rate, income per capita, income inequality, illiteracy rate, and national percent of traditional fuel use out of total fuel use.

While using this data set to examine the relationship between variation in population share using traditional biomass fuel and variation in infant and child mortality would be new, the measurement error is potentially high in the predicted household fuel use values, biasing our estimates of the effect of traditional biomass fuel on mortality toward zero. Since the effect is likely to be small, this attenuation bias may potentially eliminate any observable effect.

As a result, this thesis chooses to examine a slightly less appropriate proxy for exposure to indoor air pollution—the percent of traditional biomass fuel use out of total fuel use—because of available data for more countries and across time (1971 to 2000). While Smith et al. (2001) shows that the correlation between the percent of traditional biomass fuel use at the national level and percent of households using traditional biomass fuels is not particularly high, percent of traditional biomass fuel use is able to capture the extent to which populations have access to and use modern energy carriers such as electricity. A high share of traditional biomass fuel use reflects a population that does not have access to or cannot afford cleaner and more efficient energy carriers. This variable thus serves as a proxy for the probability that a population will be exposed to indoor air pollution.[11]

3 Macro Analysis

Dependence on traditional biomass fuels leads to adverse health effects that should increase mortality, particularly among infants and children. This effect on mortality should be visible in aggregate, national indicators such as infant mortality, child mortality, and life expectancy at birth. Indeed, Table 2 shows an increasing trend among average crude death rate, infant mortality rate, and child mortality as percent biomass fuel use increases for 162 countries in 1998.

Table 2 also shows a negative association between life expectancy and biomass fuel use. While this result is expected because life expectancy figures are generally derived from infant and child mortality rates using model life tables (World Bank 2002), the changes in life expectancy are interesting because greater traditional fuel use appears to depress female life

[11] Alternative variables were also explored such as the level of traditional biomass fuel use per capita. This variable was constructed by dividing the quantity of traditional biomass fuel use with either the rural population or the total population of the country. Regressions run with both constructed levels of traditional biomass fuel use per capita did not significantly alter the results as associations between biomass fuel use and the health indicator remained significant and directionally similar.

expectancy more. In particular, the life expectancy gap shrinks as traditional fuel use rises, which is what we would expect since females spend disproportionately more time indoors and performing activities such as cooking with high indoor particulate exposure risks.

3.1 Model Specification

We begin with a model of infant and child mortality that has been well-documented in empirical macro-level population studies. In an excellent study of fertility and mortality in developing countries, Schultz (1997) uses the relationship in Equation (1) to estimate the determinants of child mortality in a cross-country sample:

(1) $$H_{it} = \alpha_{it} + \gamma * X_{it} + \varepsilon_{it}$$

The indicator of health status *H* in the *i*-th country and the *t*-th period is assumed to be a linear function of a vector of explanatory variables *X* and disturbances ε, iid with mean of zero and constant variance σ_{ε}^{2} (plus constant α). He describes the following explanatory variables that have significant influences on child mortality (also see Schultz 1993a).[12]

(a) Women often shoulder the burden of household activities and child-rearing, particularly in developing countries. Female education is therefore an important factor in child mortality because women prepare food and provide medical care for children. In fact,

[12] While not included here, Schultz (1997) also uses the proportion of each country's population that is reported to be Catholic, Protestant, and Muslim as a proxy for the way in which culture may influence the priority of education of women. The connection between religion and mortality appears rather tenuous among individuals, however, and aggregated figures of religion are even less likely to be a determinant of mortality. As a result, these variables are not included in this analysis. Schultz also uses proportion of male labor force in agriculture as a variable because agricultural employment can increase the potential of animal diseases to spread to humans and the time to obtain medical care (Schultz 1994). However, Schultz (1993b) suggests that the proportion of male labor force in agriculture and urban population share are highly correlated and should not be used together as explanatory variables. Urban population share is used in this analysis because of available data for more countries. In addition, income inequality from the 1997 Deininger and Squire data set was initially included in the macro analysis. This specification was not reported, however, because Atkinson and Brandolini (2001) suggest that income inequality figures cannot be compared across countries because the definitions and data collection methods greatly differ. Using data from OECD countries, the authors show that income inequality data can produce misleading results when pooled together. Since data from developing countries are likely to be of even lower quality, income inequality was not included as a variable in the final macro specification.

empirical work has suggested that women's education is the most significant determinant of child mortality (Schultz 1989; Schultz 1993b). Male education is expected to have less of a direct effect on mortality because of less time spent in child-care, but can be important as a proxy for household income (Horton 1986). Male and female education are thus included as separate explanatory variables.

(b) Log of GDP per capita is used as a measure of nonhuman capital income from land, natural resources, and reproducible capital (Schultz 1993a). Schultz (1997) explains that income can be compared across countries using the purchasing power of the local currency for a broad bundle of consumer goods or foreign exchange parities that describe a nation's productivity in producing internationally tradable commodities. Income by purchasing power parity is more useful because most personal income is spent on nontradable goods. Moreover, Preston (1980) argues that life expectancy and mortality have nonlinear relationships with income per capita and presents evidence in support of a log linear relationship.

(c) Urban population share and proportion of children age one immunized for dpt (diphtheria, pertussis, and tetanus) serve as controls for health care access and disease prevalence. Populations living in urban areas generally have greater access to medical care, clean water and sanitation, and toilet facilities. At the same time, however, the high population densities and poor utilities and services in certain urban areas may have a positive effect on mortality rates. Proportion of children age one immunized for dpt serves as a control particularly for perinatal and postnatal care.

(d) Nutrition is a critical determinant of child mortality, and Schultz (1997) uses calories consumed per capita per day as a measure of nutrition. Calories consumed is not a perfect measure, however, because the caloric requirements of populations across countries may vary. Populations that are highly physically active, such as rural populations, will have higher caloric requirements, and countries with a larger rural population may have a higher caloric requirement (Willet 2003). Caloric requirements also vary by weight and height. As a result, differences in calories consumed may not actually reflect differences in nutritional levels. Several researchers have used calories per day as a measure of nutrition and find that it is negatively associated with mortality, particularly at low levels of income (Fogel 1990; Strauss 1993). Schultz (1997) allows the effect of calories consumed to vary by calorie level through the inclusion of exponential terms in calories and finds that a quadratic form is appropriate in cross-country data.

Both cross-sectional and within-country models will follow the model specification by Schultz (1997) using the same variables and functional forms with the additional explanatory variable of biomass fuel use. The cross-sectional relationship is shown in Equation (2):

(2) $$H_i = \alpha_i + \beta * BF_i + \gamma * X_i + \varepsilon_i$$

The variables are the same as in Equation (1) with the addition of percent biomass fuel use out of total fuel use *BF*, in the *i*-th country. The within-country relationship is shown in Equation (3):

(3) $$H_{it} = \beta * BF_{it} + \gamma * X_{it} + \lambda_i + \delta_t + \varepsilon_{it}$$

where the indicator of health status *H* in the *i*-th country and the *t*-th period is assumed to be a linear function of percent biomass fuel use out of total fuel use *BF*, a vector of explanatory variables *X*, a country-specific effect λ, a time-specific effect δ, and disturbances ε, iid with mean of zero and constant variance σ_{ε}^2. The indicators of health status *H* in both models will be infant mortality, child mortality (defined as probability of dying before age 5), life expectancy, life expectancy by sex, and life expectancy gap (of female life expectancy minus male life expectancy).

3.2 Potential Biases

The main concern in this new model is with omitted variables and simultaneity bias. With omitted variables, a statistically significant relationship between biomass fuel use and health may actually be incidental because the variation in biomass fuel use is picking up the effect of an omitted variable. Using the above mortality model outlined by Schultz (1997) helps to resolve this issue.

Simultaneity bias is a larger concern as income may be an endogenous variable. In the model outlined in Equation (2) and (3), a causal relationship from income to health is assumed where a higher log of GDP per capita represents a wealthier population that can afford better energy, housing, food, and health care. Empirical research has shown strong correlations between wealth and health (Ettner 1996; Pritchett and Summers 1996; Smith 1999), and a causal link between the two has been widely accepted. Reverse causality is an important concern, however, as better health may also lead to higher productivity and higher income per capita (Bloom and Williamson 1998; Bloom and Canning 2000; Bloom et al. 2001; Commission on Macroeconomics and Health 2001).

Various instrumental variables (IV) have been used in attempts to tease out the exact relationship between health and wealth (Pritchett and Summers 1996; Ettner 1996; Bloom et al. 2001), but many of the instruments are rather weak as they are often still related to health. Strauss and Thomas (1998) thus conclude in an excellent review that health and income are clearly correlated, but that the exact relationships between health and income are still unclear.

A reverse causation may also exist between education and health where better health increases educational performance and school participation (Jamison and Leslie 1990; Miguel and Kremer 2000). A review by Behrman (1996), however, states that evidence on the causal effect of health on education is inconclusive. With both education and income, although the assumption is somewhat tenuous, this thesis will follow the mortality model specified by Schultz (1997) and include both income and education as exogenous variables.[13]

3.3 Data

Global biomass fuel data are from the United Nations Statistics Division and International Energy Agency. Additional data are from the World Development Indicators, Barro and Lee (2000), Penn-World Table, and Food and Agricultural Organization. Appendix 1 lists the source of data for each variable.

3.4 Estimation and Results

3.4.1 Cross-Sectional Results

Table 3 shows the OLS results of estimating Equation (2) in the year 1998 using White's heteroskedasticity consistent standard errors. The first column shows that biomass fuel use, income, proportion of children immunized, and both calorie variables have statistically significant effects on infant mortality. The estimate on biomass fuel use is rather precise with a standard error of only 0.0843 and suggests that a 10 percentage-point increase in the percent of biomass fuel use increases the infant mortality rate by 2.25 deaths per 1,000 live births. The

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[13] A recent working paper by Meer et al. (2003) uses inheritance as an instrument and finds that the estimate of the effect of wealth on health at the individual level becomes insignificant with instrumental variables. Receipt of an inheritance is a strong instrument because it is correlated with a change in an individual's wealth, but is unlikely to be related to changes in health, conditional on initial health status. With this evidence, the authors conclude that in the short-run, wealth does not significantly influence health. National indicators of wealth are different from individual indicators because variations in aggregate data can reflect different levels of public health infrastructure, medical care, and sanitation. Thus, indicators of wealth may still significantly influence health in aggregate data. Without additional macro studies that suggest an incidental relationship from wealth to health, income is still included in the mortality model.

results roughly replicate those found by Schultz (1997), except that the estimate for the effect of female education is insignificantly different from zero. However, high correlation between years of female education and years of male education may be causing the high standard errors. The inclusion of both female and male education variables in conjunction with other determinants may also be producing the unexpected positive point estimate for female education.[14] When female and male education are regressed on infant and child mortality with only biomass fuel use as an additional explanatory variable, the effect of female education is significant, negative, and much larger in magnitude than the effect of male education. This result replicates evidence from empirical studies that suggest female education is the primary determinant of child mortality.[15]

Using child mortality as the dependent variable in Column 2 gives similar results, but the positive estimate on biomass fuel use is even more precise. The regression shows that a 10 percentage-point increase in the percent of biomass fuel use raises the child mortality rate by 7.2 deaths per 1,000 live births, an effect larger than the 4.9 deaths per 1,000 live births calculated by Bloom and Zaidi (2002) with this increase in fuel use. The implication is that reducing the percent of biomass fuel use for a country such as Kenya from 76.2 percent to zero would reduce its child mortality rate by 38 percent and prevent 54,000 deaths of children before age 5 in a five year span.[16]

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[14] Schultz (1997) uses both female and male education as variables in his cross-country regressions and finds a highly significant and large negative association between female education and child mortality. Attempts to replicate this result by not including biomass fuel use and using the same variables and functional forms were unsuccessful. The source data for all variables in this analysis is the same (although updated) except for education, where the Barro-Lee data set is used. Regressions with World Bank education data, which Schultz (1997) uses, produced the same insignificant coefficient on female education. This result is expected since the Barro-Lee data are extremely similar.

[15] Different model specifications with female education also showed significant, negative associations between female education and infant and child mortality.

[16] Biomass fuel use figure from United Nations (1998). Deaths calculated using Kenya's crude birth rate (34.58 per 1,000 people) and total population (28.7 million people) in 1998 from the World Development Indicators (World Bank 2002).

Interestingly, the estimated effect of biomass fuel use on child mortality is proportionally greater than the estimate on infant mortality when compared to their respective dependent variable means—e.g. in Column 2, the estimated coefficient for biomass fuel use is 0.717, which is 1.25 percent of the mean child mortality rate of 57.2 deaths per 1,000 live births. This disproportionate effect on children before age 5 as opposed to infants before age one suggests that children may have greater exposures to indoor air pollution after infancy or that the effects of indoor air pollution on mortality are only dominant in comparison to other factors after prolonged exposure. Infants before age one are more susceptible to disease and death than children between ages one and five, and other factors may be more significant as determinants of infant mortality.

As expected, the regressions with life expectancy dependent variables in Columns 3 through 5 have relatively similar results because life expectancies are calculated based on infant and child mortality rates. Again, biomass fuel use, income, proportion of children immunized, and both calorie variables have significant effects on mortality. Column 3 shows that a 10 percentage-point increase in biomass fuel use depresses life expectancy by 8.7 years, a substantial reduction. Comparing Columns 4 and 5, the results show that biomass fuel use has a slightly larger negative effect on male life expectancy, although the difference is not statistically significant. Indeed, the estimate for the effect of biomass fuel use on the life expectancy gap in Column 6 is insignificantly different from zero. Variation in life expectancy gap appears to be explained mostly by female and male education, income, urban population share, and nutritional level. These results do not confirm the finding by Bloom and Zaidi (2002) that biomass fuel use depresses female life expectancy more than life expectancy.

Overall, Table 3 shows that the estimates by Bloom and Zaidi (2002) are robust to the addition of relevant determinants of infant and child mortality. The regressions show that the percent biomass fuel use of a country has a substantial effect on its infant and child mortality rates and life expectancy. These results support epidemiological research which has found a causal relationship from indoor air pollution from traditional biomass fuel to ALRI and COPD.

3.4.2 Panel Results

Table 4 shows the regression results using OLS, fixed-effect, and random-effect estimators on panel data of non-OECD countries with IEA energy data. Comparisons cannot be made directly between the cross-sectional and panel estimates because the source of the biomass fuel use figures, the number of countries, and the type of countries differ, but the OLS estimates on biomass fuel use, income, urban population share, and nutrition in the first and second columns are similarly significant and in the same direction as before.[17] In both Columns 1 and 2 though, female education now has a significant, negative association with infant and child mortality, as empirical research suggests.

Column 1 also shows that biomass fuel use is positively associated with the infant mortality rate, but to a much smaller degree than before. Now a 10 percentage-point increase in biomass fuel use is estimated to raise the infant mortality rate by only 0.12 deaths per 1,000 live births. As the estimate is highly precise, the implication is that reducing the sample to only non-OECD countries and/or controlling for time-specific effects greatly reduce the magnitude of the effect of biomass fuel use. Likewise, the estimate on biomass fuel use in the second column is precise but shows a very small effect on child mortality.

[17] The model specification is also slightly different as the proportion of children immunized for dpt is not included as a variable in the panel data set because figures are only available from 1980 to 1999. This should have less of an effect on the estimates.

To help determine whether the smaller effect is a result of the exclusion of countries or data across time, OLS regressions were conducted using the UN energy data with a sample of only non-OECD countries. The results showed that the exclusion of OECD countries appears to somewhat reduce the estimated effect of biomass fuel use on mortality as well as increase the standard errors because of the smaller sample size. The panel OLS estimates, however, are miniscule, suggesting that the availability of data across time is the dominant factor in reducing the effect.

More importantly, we are interested in accounting for unobserved country-specific effects. When these effects are taken into account in Columns 3 through 6, the effect of biomass fuel use becomes insignificant, except for the random effects estimate with child mortality rate as the dependent variable. The Hausman test of whether the estimated coefficients from random and fixed effect estimators differ systematically has a χ^2 statistic of 113.2 for the infant mortality rate regression and a χ^2 statistic of 76.9 for the child mortality regression. These test statistic values lead us to reject the null hypothesis that the country-specific effects are uncorrelated with the explanatory variables and use the fixed-effect estimates.

The within-country analysis in Columns 3 and 4 show small and insignificant estimates on biomass fuel use, suggesting that biomass fuel use has little effect on the infant or child mortality rate. These results, which are different from the cross-sectional estimates, are likely due to measurement error from the low quality of data from Africa and South Asia, and also from the extrapolation of data to form a historical time-series.

Table 5 shows OLS and fixed-effect estimates of the effect of biomass fuel use on different life expectancy indicators.[18] Column 1 shows a negative and significant association between biomass fuel use and life expectancy. This effect is miniscule; however, as a 10 percentage-point increase in biomass fuel use lowers life expectancy by only 0.02 years. Interestingly, the estimate on female education is positive and significant, the expected relationship. Columns 2 through 4 show that biomass fuel use depresses male life expectancy more than female life expectancy to a statistically significant degree. However, this gender differential is extremely small in magnitude.

Unobserved country heterogeneity is once again important in our sample as the Hausman test rejects the null hypothesis that the country-specific effects are uncorrelated with the explanatory variables for the regressions with life expectancy, male life expectancy, female life expectancy, and life expectancy gap (χ^2 statistics of 70.5, 61.2, 72.6, and 45.2, respectively). For this reason, only fixed-effect estimates are reported. Interestingly, the coefficients in Columns 5 through 7 are all positive and significant, suggesting that greater biomass fuel use increases life expectancy. These positive associations are likely the result of measurement error from constructed values of life expectancy or low quality biomass fuel use data from Africa or South Asian countries. Moreover, the variation of biomass fuel use within countries may be incidentally correlated with the variation in life expectancy. The results in Column 8 also support the OLS results in Column 4 that biomass fuel use decreases the life expectancy of males more than females to a statistically significant degree. Again, however, the difference is extremely small.

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[18] Random-effect estimates are not shown because the Hausman test suggests that country-specific effects are correlated with the explanatory variables.

Overall, the results in Tables 4 and 5 show that when country-specific effects are accounted for, biomass fuel use has little effect on infant mortality, child mortality, and life expectancy. However, these small and insignificant estimates are potentially the result of measurement error from extrapolated historical time-series data for biomass fuel use. Since these extrapolated time-series are often constructed from low quality data, the measurement error can be substantial. Moreover, measurement error is magnified when estimating coefficients in the within dimension (Griliches and Hausman 1986), perhaps explaining the miniscule estimates obtained in the fixed-effect analysis.

4 Micro Analysis

The preceding section examined the effect of biomass fuel use on mortality using aggregate cross-country data. After finding a significant, positive effect on mortality, we now turn to household level data because they are generally richer and provide the opportunity to control for more variables that may influence mortality and exposure to indoor air pollution. As a result, micro data allow for the analysis of more tightly specified hypotheses. Moreover, micro data reflect the variation in biomass use within a country, which was not captured by our aggregate fuel variable.

4.1 Data

In this section, micro data from the 1991 Pakistan Integrated Household Survey (PIHS) are analyzed because they have the most detail concerning traditional biomass fuel use out of all World Bank Living Standard Measurement Study (LSMS) household surveys. A total of 4,798 households were surveyed, and ever-married women between the ages of 14 and 50 were asked about her total number of births, when the child was born, the sex of the child, whether the child is still alive, and how long the child lived if dead. Conception prior to marriage is not common or socially acceptable in Pakistan, so excluding unmarried women from our sample is unlikely to bias our results. In total, the maternity histories for 4,811 women from 3,811 households were available, for a sample of 24,199 children ever born.

A variety of questions in the survey concerned traditional biomass fuel use and potential exposure to indoor air pollution. All households indicated their "main cooking fuel" out of electricity, natural gas, cylinder gas, charcoal, coal, kerosene, firewood, dung, and other biomass. As cooking is the primary use for biomass fuels in Pakistan (Anwer 2001) and also exposes individuals to high-intensity pollution episodes (Ezzati and Kammen 2002a), a household's use of firewood, dung, or other biomass should be closely associated with exposure to indoor air pollution, and subsequently, mortality. Indeed, Table 6 shows that cooking with traditional biomass fuels is negatively associated with both infant and child mortality in the Pakistan sample. The association with child mortality appears to be stronger as cooking primarily with traditional biomass fuels increases the probability of a child dying before age 5 by 5.9 percentage points, while the increase is only 1.7 percentage points with infant mortality. This evidence seems to support results from the cross-sectional macro analysis that traditional biomass fuel use affects mortality, with disproportionate effects on children, but before drawing any conclusions, it is necessary to account for confounding factors through multiple regression analysis.

The regressions will utilize the energy variable of cooking primarily with traditional biomass fuels. In addition, households reported the frequency of firewood, dung, and other biomass usage (separately) in a typical day in the past month. Substantially fewer households used dung and other biomass so only the frequency of firewood is used as a variable in addition to whether a household uses traditional biomass fuels.

4.2 Micro Literature

Microeconomic studies have not yet examined the relationship between traditional biomass fuels and mortality. Using household data from the Pakistan Integrated Household Survey (PIHS), Bloom et al. (1997) have studied the effect on morbidity and show that biomass fuel use has a positive and significant effect on whether an individual reports cough, flu, or fever in the last 30 days. While their results corroborate those found in epidemiological studies, their estimates are potentially biased as their health indicator likely suffers from measurement error because it is not a direct health measurement. More importantly, their work does not provide a framework or model to analyze the effects of biomass fuel use on mortality.

4.3 Model Specification

Based on economic literature and the nature of available data in the PIHS, a logit model will be used to estimate the probability that a child dies before the age of 5 and the probability that a child dies before the age of 1:

(4) $$y_i* = \alpha_i + \beta * BF_i + \gamma * X_i + \varepsilon_i, \quad y = 1[y* > 0]$$

In Equation (4), the probability that a child dies $y*$ is a latent variable, which is a function of traditional biomass fuel use *BF*, a vector of exogenous explanatory variables *X*, and disturbances ε. The latent variable $y*$ is unobserved, and instead, the dichotomous variable of child death *y* is observed where *y* is one if $y* > 0$ and *y* is zero if $y* \leq 0$. The cumulative distribution of ε is logistic. The following variables are included as exogenous explanatory variables *X*:

(a) It is well established that the biological risk of death is higher for male than female infants (Panis and Lillard 1994). The sex of the child, which is a dummy variable of one if the child is female and zero if the child is male, would thus be expected to have a negative effect on child mortality. However, sex preferences that may influence mortality risks would also be captured with this variable, resulting in an effect on mortality in the opposite direction. In particular, Gangadharan and Maitra (2000) show that higher mortality for girls between the ages of one and five in Pakistan potentially reflect discrimination against girls.

(b) Biomedical studies have shown that maternal age at birth has significant influences on pregnancy outcome and child mortality through effects on maternal health (Mosley and Chen 1984). A child's health endowment is expected to decline with increases in maternal age. At the same time though, a mother's experience in health production tends to increase with her age (Wolfe and Behrman 1982). To allow for possible nonlinear effects of maternal age on child mortality, the square of this variable is also included (Pitt 1997).

(c) The child's year of birth is included to capture a time trend in child mortality.

(d) As in the macro analysis, female education is a critical determinant of child mortality. In fact, consistent micro evidence of the negative association between mother's schooling and child mortality has led to a universal acceptance of this relationship (Schultz 1989). A father's education will be included as a proxy for his income (Horton 1986) and also to reflect his preferences over child health and consumption. Education is measured as the highest completed grade of schooling from zero to graduate school as grade 15.

(e) Household constraints of income and prices will be represented by the log of total monthly expenditures and the prices of three common foods—rice, masoor (lentil), and eggs. All values are in Pakistan rupees. Total monthly expenditures are used rather than income because incomes can be quite variable in rural households. Since households are likely to smooth consumption in the face of income fluctuations, expenditures will be a better proxy for average income than actual income in a given period (Chaudhuri and Pfaff 2002). However, the expenditures variable may still be subject to measurement error, so an alternative proxy representing a household's nonhuman capital assets will be tested. The log of a father's wage will be represented according to the human capital model by Mincer (1974):

(5) $\log w = \alpha + \beta * Educ + \gamma * Exp + \delta * Exp^2$

where the log of earnings *w* is a function of years of schooling *Educ*, potential experience *Exp*, and potential experience squared Exp^2. Experience is measured as:

(6) $Exp = Age - Educ - 6$

(f) Household variables of whether any type of sanitation system and toilet existed were also included as proxies for local public services and household and community characteristics that may influence the risk of mortality. In addition, dummy variables for rural areas and the provinces of Sindh, NWFP, and Balochistan were also included to capture any other community characteristics that may be specific to a rural or provincial area.

Three empirical issues need to be addressed with this specification. First, substantial evidence has shown that parents perceive the inherent healthiness of a child through knowledge of their own genetic endowments and health characteristics of the household and neighborhood (Olsen and Wolpin 1983; Rosenzweig 1986; Panis and Lillard 1994). If parents perceive that their child's inherent healthiness is low, they may alter their fertility decisions, leading to selection bias in the sample of potential births (Pitt 1997). To address this, Pitt (1995) uses a sample of only first births, which he argues are exogenous because women in developing countries all tend to give birth to at least one child. The resulting sample of first births reflects the full distribution of women and is therefore not self-selected. Our sample will likewise include only first births to account for fertility selection bias.

Second, a child's inherent healthiness can also influence parents' choice of health inputs leading to another source of self-selection bias (Rosenzweig and Schultz 1983; Panis and Lillard 1994). For example, Panis and Lillard (1994) suggest that a woman with poor health may believe she will have a less healthy child and seek prenatal care, leading to adverse self-selection of women who seek prenatal care.[19] The resulting estimate of the effect of prenatal care on child health would thus be biased toward zero.

To some extent, this bias is reduced by restricting the sample to first births because a couple has less information on the inherent health endowment of their future child. However, the bias is still potentially significant as a woman may perceive her future child's health endowment through information such as her mother's reproductive history or hereditary diseases. This information may be known to the woman but unknown to the researcher. As a result, she may still alter her choice of health inputs based on unobserved health endowments. Fortunately, we would not expect self-selection to significantly influence our primary variable of interest, traditional biomass fuel use, as costs are likely the primary factor in a household's choice of energy carriers (Reddy and Reddy 1994). Moreover, since the health impacts of indoor air pollution may not be widely known or appropriately characterized, households would not be expected to alter their fuel choices based on knowledge of unobserved health endowments.

Third, censored data may bias our estimates. The survey sample includes infants who have not yet reached the age of one and children who have not yet reached the age of five by the time of the survey. Since some of these infants and children may die after the time of the survey during their infanthood or childhood, respectively, these censored observations will bias our

[19] Favorable self-selection, in the opposite direction, may also result.

estimates of the effects on infant and child mortality. As a result, all infants born within one year and children born within five years of the survey are excluded from our sample.[20]

Table 7 contains descriptive statistics for all right-hand side variables including traditional biomass fuel use variables in the infant sample. Sample means and standard deviations are fairly similar for the child sample. The variables are categorized by their level of aggregation—from individual to household-level to community-level.

4.4 Estimation and Results

Determinants of child mortality are analyzed first because child mortality is inclusive of infant mortality (deaths before the age of five include deaths before the age of one), providing a larger sample of deaths from which to examine potential determinants. Table 8 shows the logit estimates for determinants of child mortality using cluster standard errors. Potential correlations may exist among households in the same sample unit because the PIHS sample was collected with a multi-stage stratified sampling procedure that involved picking a cluster of households at some stage. The sample is therefore not a simple random sample, and ignoring this cluster effect would underestimate the standard errors.

The first column in Table 8 uses monthly expenditures as a proxy for average income and produces results similar to those found in other microeconomic studies of mortality. Maternal age, mother's education, and monthly expenditures all have significant, negative associations with child mortality. Female sex of the child also has a negative association with child mortality, although the estimate is less precise. In addition, Column 1 shows that the additional variable we include in our model—cooking with a traditional biomass fuel—has a positive, but not

[20] This exclusion did not lead to a significant loss of information. The infant sample of first births lost 163 observations for a final sample of 4,453 infants. The child sample lost 881 observations for a final sample of 3,776 children. Regression results including the censored observations were relatively similar to those reported here, although the coefficient on traditional biomass fuel use was slightly more precise.

particularly precise, estimated effect on child mortality. The estimate is significant at the 10 percent, but not 5 percent level.

Although imprecise, the positive coefficient on traditional biomass fuel in a model including various explanatory variables is still meaningful. The magnitude of the coefficient can be calculated by using the estimated coefficients from Column 1. For a household that does not use traditional biomass fuels and has all other characteristics equal to the sample means, the probability of a child dying is 12.0 percent.[21] The predicted difference in probability of a child dying before the age of five in a household that primarily cooks with traditional biomass fuels, as opposed to one that does not, is 2.9 percentage points. Assuming that approximately 4.7 million children are born each year in Pakistan and that 85 percent of households in Pakistan use traditional biomass fuels (World Bank and Energy Sector Management Assistance Programme 1993), an effect of this magnitude would translate into 116,000 *more* deaths of children before age 5 in a five year span in the entire country.[22] For this rough calculation, I assume that 85 percent of the children born each year are born in households that use traditional biomass fuels.

Column 3 uses the number of times firewood is used in a typical day instead of a traditional biomass fuel dummy resulting in similar estimates and statistical precision as Column 1. The estimated effect on the number of times firewood is used in a typical day is more precise than that for the fuel variable in Column 1, which is likely because the variable is not a dummy. The results show that the predicted marginal effect of using firewood one more time a day on the probability of a child dying, assuming that all other characteristics are equal to the sample means,

[21] The sample is the 2,408 observations in the regression in Column 1.
[22] Deaths calculated using Pakistan's crude birth rate (33.82 per 1,000 people) and total population (138 million people) in 2000 from the World Development Indicators (World Bank 2002).

is 1.0 percentage point.[23] The average household in this regression sample uses firewood 1.8 times a day, but some households use firewood up to 7 times a day. For households using firewood 7 times a day, their probability of a child dying before age 5 would increase by 5.3 percentage points over an average household.

To control for potential measurement bias in our income proxy, experience and experience squared were used instead of the log of monthly expenditures in Columns 2 and 4 to proxy for a father's log wage. The results are almost identical to those in Columns 1 and 3, respectively, with similar estimates and precision on all variables. In particular, the estimates on the fuel variables are extremely similar in magnitude and precision, suggesting that our estimated coefficients on traditional biomass fuel are fairly robust to measurement error in the income variable.

In the fifth column, the sample is restricted to only rural households to see if the way they use traditional biomass fuels may have a different effect on mortality. Indeed, the results show that the magnitude of the estimated effect on firewood usage is larger than for all households as in Columns 3 and 4. The standard errors are slightly larger as well, but the statistical precision is similar with the estimate still significant at the 10 percent level. Using the regression coefficients and sample means, the predicted marginal effect of using firewood one more time a day on the probability of a child dying in rural households, assuming that all other characteristics are equal to the sample means, is 1.8 percentage points.[24] This estimated marginal effect is larger than that from Column 3, suggesting that rural households may use traditional biomass fuels more inefficiently or for longer periods each time, generating more indoor air pollution and

[23] The predicted marginal effect is calculated using the estimated coefficients and sample of 2,330 observations from the regression in Column 3.
[24] The predicted marginal effect is calculated using the estimated coefficients and sample of 1,035 observations from the regression in Column 5.

increasing the marginal risk of child mortality. While the estimates are not highly precise, overall the results in Table 8 corroborate the macro results and suggest that traditional biomass fuel use increases the risk of child mortality.

Table 9 shows that the effects of various determinants are slightly different on infant mortality. As infants before age one are more susceptible to disease and death than children between ages one and five, the factors significant as determinants of infant mortality may be different than those for child mortality. In particular, the magnitudes of the estimates on female sex of the child and the year of the child's birth in the first and second columns are much larger. These effects on mortality are therefore more significant, as the statistical precision is fairly similar to that in Table 8. The larger estimate on female sex of the child supports studies that male infants before age one have a biologically higher risk of mortality than females. The larger estimate for year of child's birth may be capturing changes in public health measures or medical care over time that may be more significant in helping children survive past the age of one.

While these child variable estimates are larger, the estimates on cooking with traditional biomass fuel in Column 1 and the number of times firewood is used in a typical day in Column 2 are about half as large as before. Now the estimates on both these fuel variables are insignificantly different from zero, suggesting that traditional biomass fuel use has no significant effect on infant mortality. These results may be imprecise because the number of first-born infants death is rather small. Alternatively, the results may support those from the cross-sectional macro analysis, where the estimated effect on child mortality was larger and more significant than the effect on the infant mortality. Thus, the micro data may suggest that children have greater exposures to indoor air pollution after infancy or that the effects of indoor air pollution on mortality are only significant after infancy.

The results from the alternative specification with a proxy for a father's log wage were not reported for infant mortality, although the estimates were again similar to those using the log of monthly expenditures. Column 3 shows the results when restricting the sample to only rural households. While there is likewise an increase in the estimated effect of firewood usage from the sample of all households in Column 2, the larger standard errors render the estimate statistically insignificant. Overall then, the results in Table 9 show that traditional biomass fuel use may have a small positive association with infant mortality, but the effects are highly insignificant.

5 Conclusion

Epidemiological studies have shown consistent evidence that indoor air pollution from traditional biomass fuels leads to increased morbidity, but few studies in any discipline have examined the effects on mortality. This thesis finds evidence at the country and household levels that the use of traditional biomass fuels substantially increases the risk of child mortality. In particular, the cross-sectional results of macro data show that a 10 percentage-point decrease in the share of energy consumption due to biomass fuels for a country lowers the child mortality rate by roughly 7.2 deaths per 1,000 live births. This substantial, significant estimate is somewhat surprising, particularly since Bloom and Zaidi (2000) estimate a decrease in child mortality of 4.9 deaths per 1,000 live births using a much simpler regression model. For a country such as Kenya, in which roughly three-fourths of total energy consumption is supplied by biomass fuels, the implication is that switching completely to non-biomass fuels would, *ceteris paribus*, lower its child mortality rate by 38 percent and prevent 54,000 deaths to children before the age of five over five years. While the estimate at the household level (based on data from Pakistan) is less well-determined, it similarly shows a positive relationship with child mortality that supports the macro results.

These estimates of the mortality effect of traditional biomass use, applied on a global level, are alarming. Table 10 shows that among countries with the highest HIV/AIDS prevalence, eliminating the use of traditional biomass fuels could lead to differences in life expectancy on par with differences attributed to the HIV/AIDS epidemic. In Rwanda, traditional biomass use depresses life expectancy by approximately 7.8 years, while the HIV/AIDS epidemic has lowered life expectancy by approximately 9.7 years. While HIV/AIDS has reached epidemic proportions in numerous countries and will continue to spread if left unchecked, the table shows that current household energy use in developing countries presents a substantial public health risk. In conjunction with evidence from epidemiological studies of the various diseases associated with indoor air pollution, a concerted global effort is therefore needed to address this issue, particularly because of the complex relationships between energy, health, and poverty.

The World Summit on Sustainable Development in Johannesburg highlighted the importance of clean, efficient household fuels and the health effects of indoor air pollution, but the dialogue and action must continue. Effectively reducing the impact of indoor air pollution from traditional biomass fuels will require a combination of research, advocacy, increased awareness, interventions, and policies (World Health Organization 2002). Research and awareness are the first steps, as the health impacts of indoor air exposure and biomass fuels must be clearly understood. A wide range of interventions have been identified such as using improved stoves, increasing ventilation, educating individuals to change their behavior, or increasing the availability of cleaner fuels. However, significant research is still required to evaluate the effectiveness of these interventions in local communities, as well as the costs and benefits.

In particular, research should focus on household fuel-choice decisions given the complex relationship between energy and poverty. Reddy and Reddy (1994) show that available short-term income is the primary factor in household fuel-choice decisions, but whether this holds if family members understand the health risks associated with indoor air pollution is unclear. If price is critical, altering the pricing schemes of energy carriers may also have an effect on fuel choice.

Indoor air pollution is a serious public health risk, particularly for women and young children. Moreover, failure to address this issue can reinforce global poverty conditions and preclude opportunities for development. Successful interventions and policies have important implications for the quality of life for billions around the world, as decreasing indoor air emissions can improve health, worker productivity, education levels, and the environment.

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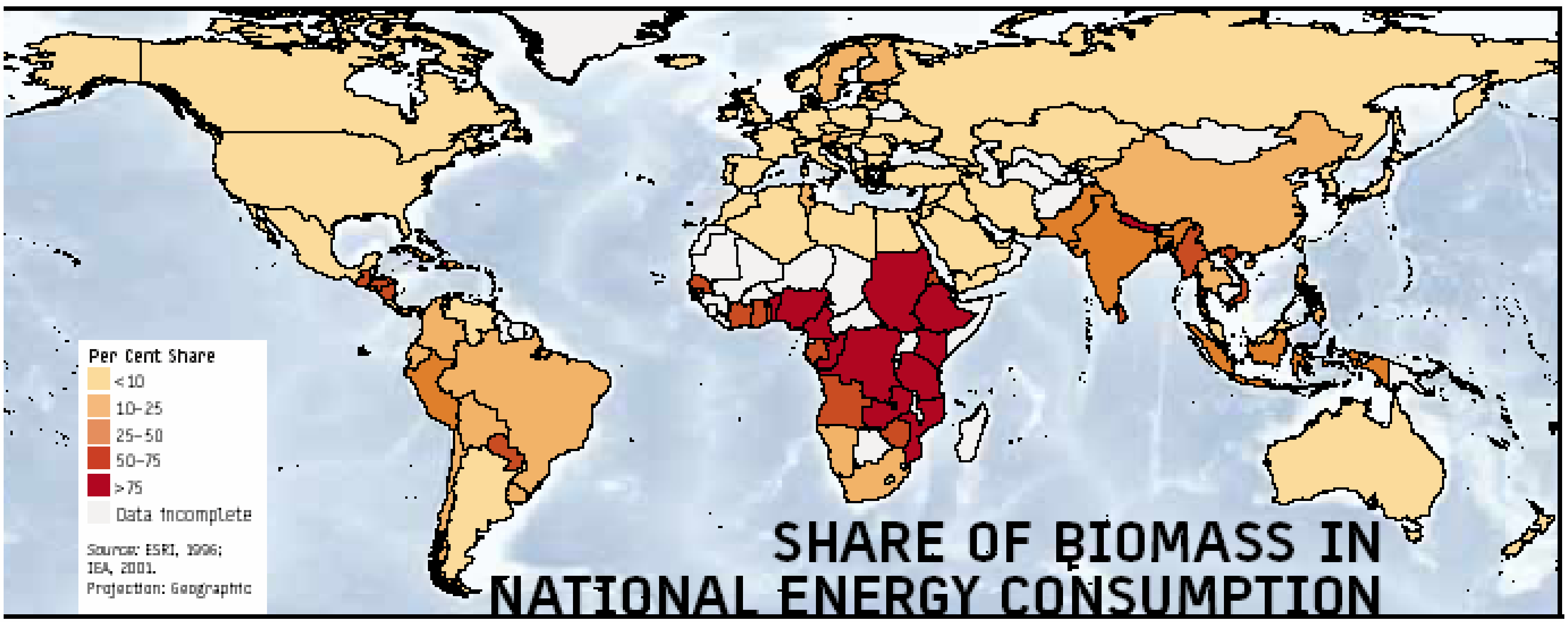
Figure 1. *Share of Traditional Biomass Fuel in National Energy Consumption*.



Reproduced from United Nations (2002).

Table 1. *Range of levels of particulates (PM10) and carbon monoxide found in studies of indoor air pollution in developing countries, and comparison with WHO and USEPA air quality guidelines.*

	Range of ambient levels in LDC studies for simple stoves		WHO and USEPA guidelines		
Pollutant:	Period	Level	Period	WHO	EPA
Particulates less than 10 microns in aerodynamic diameter (PM10 in $\mu g/m^3$)	Annual	Not available, but expect similar to 24 hour	Annual	Guidance presented as exposure-outcome relationships	50
	24 hour	300-3,000+	24 hour		150 (99th percentile)
	During use of stove	300-3000+			
Carbon monoxide (CO in parts per million – ppm)	24 hour	2-50+	8 hour	10	9
	During stove use	10-500+	1 hour	30	35
			15 minutes	100	
	Carboxy-haemoglobin	1.5-13%	Carboxy-haemoglobin	Critical level<2.5% Typical smoker: 10%	

Reproduced from Schirnding et al. (2002).

Table 2. *Average Mortality, Fertility, and Life Expectancy, by Percent Biomass Fuel Use, 1998*

	Percent Biomass Fuel Use (of Total Fuel Use)				
	0-20	20-40	40-60	60-80	80-100
Number of Countries	89	23	15	13	22
Total Population (in billions)	4.02	0.84	0.34	0.31	0.32
Avg Population (in millions)	45.2	36.4	22.6	23.7	14.7
Crude Death Rate	8.0	8.3	10.4	13.5	17.5
Infant Mortality Rate	20.4	30.4	56.1	86.6	102.7
Child Mortality Rate	26.8	41.7	88.6	148.9	177.7
Crude Birth Rate	17.4	22.6	32.9	36.9	42.5
Total Fertility Rate	2.3	2.8	4.4	5.0	5.8
Life Expectancy	72.0	68.2	60.8	52.3	46.7
Male Life Expectancy	69.3	65.6	59.0	51.1	45.7
Female Life Expectancy	74.9	71.0	62.7	53.6	47.7
Life Expectancy Gap (F-M)	5.6	5.3	3.7	2.5	2.0

Notes: Percent Biomass Fuel Use is calculated from Table 4, *Energy Statistics Yearbook*, United Nations (1998). Percent biomass fuel use is defined as the percentage usage of fuelwood, charcoal, bagasse, animal, vegetal and other wastes out of total fuel use. Demographic data is from *World Development Indicators*, World Bank (2002). Demographic data are available for the number of countries reported for all indicators except for child mortality, which had several missing values. The numbers of countries with available child mortality values are 85, 21, 14, 10, 21, 151, 26, respectively, across the row.

Table 3. *Cross-sectional regressions of the percent of biomass fuel use on mortality and life expectancy, OLS Estimates, 1998*.

Dependent variable:	(1) Infant mortality rate	(2) Child mortality rate	(3) Life expectancy	(4) Male life expectancy	(5) Female life expectancy	(6) Life expectancy gap (F-M)
Means:	38.0	57.2	66.6	64.4	68.9	4.56
(SD):	<35.9>	<63.4>	<11.8>	<11.1>	<12.6>	<2.14>
Percent of biomass	0.225	0.717	-0.0869	-0.0901	-0.0834	0.00667
fuel use	(0.0843)	(0.143)	(0.0333)	(0.0327)	(0.0345)	(0.00873)
Years of female	1.42	6.06	-0.788	-0.990	-0.576	0.413
education (2000)	(2.81)	(4.50)	(1.08)	(1.06)	(1.11)	(0.257)
Years of male	-2.46	-5.19	0.530	0.808	0.238	-0.570
education (2000)	(2.90)	(4.44)	(1.13)	(1.10)	(1.16)	(0.211)
Log of GDP per	-20.0	-40.2	6.94	6.46	7.43	0.970
capita	(3.80)	(7.58)	(1.25)	(1.25)	(1.32)	(0.528)
Urban % of	-0.106	-0.0965	0.0548	0.0439	0.0663	0.0224
population	(0.132)	(0.231)	(0.0464)	(0.0454)	(0.0483)	(0.0134)
% children age one	-0.273	-0.794	0.0758	0.0768	0.0747	-0.00206
immunized for dpt	(0.119)	(0.260)	(0.0389)	(0.0372)	(0.0413)	(0.0106)
Calories consumed	-0.104	-0.151	0.0401	0.0361	0.0443	0.00817
per capita per day	(0.0454)	(0.0774)	(0.0162)	(0.0157)	(0.0169)	(0.00340)
Calories per capita	0.0197	0.0322	-0.00733	-0.00670	-0.00799	-0.00129
squared * 10^{-3}	(0.00744)	(0.0125)	(0.00252)	(0.00246)	(0.00261)	(0.000564)
R^2	0.873	0.869	0.857	0.845	0.863	0.586
F	63.7	51.9	138	132	132	17.6
# Countries	85	84	85	85	85	85

Notes: White's heteroskedasticity consistent standard errors are in parentheses. Standard deviations are in angled brackets. Variables are from the year 1998 except the two marked (2000) from the year 2000. Each regression also includes a constant term. Child mortality rate is the under-five mortality rate. The number of countries differs for child mortality rate in column 2 because a value is missing for the Republic of Congo. Biomass fuels are defined by the UN as fuelwood, charcoal, bagasse, and animal, vegetal, and other wastes. For sources, see Appendix 3.

Table 4. *The effect of the percent of biomass fuel use on infant and child mortality in non-OECD countries; OLS, fixed effect, and random effect estimates, 1972-2000.*

Dependent variable:	(1) Infant mortality rate	(2) Child mortality rate	(3) Infant mortality rate	(4) Child mortality rate	(5) Infant mortality rate	(6) Child mortality rate
Estimation Method:	OLS	OLS	Fixed	Fixed	Random	Random
Explanatory variables:						
Percent of biomass fuel use	0.0118 (0.00198)	0.0279 (0.00599)	-0.00327 (0.00238)	0.000700 (0.00553)	0.00127 (0.00241)	0.0131 (0.00552)
Years of female education (2000)	-10.0 (1.25)	-12.6 (2.84)	6.11 (1.51)	13.4 (4.73)	0.108 (1.40)	-5.33 (3.57)
Years of male education (2000)	0.449 (1.33)	1.26 (2.89)	-4.37 (1.28)	-7.38 (4.00)	-3.51 (1.27)	-2.66 (3.41)
Log of GDP per capita	-3.86 (2.23)	-20.4 (6.24)	2.11 (2.05)	0.412 (6.51)	-0.279 (2.03)	-14.4 (5.81)
Urban % of population	0.131 (0.0562)	-0.172 (0.140)	-0.502 (0.164)	-0.143 (0.487)	-0.587 (0.108)	-0.338 (0.235)
Calories consumed per capita per day	-0.203 (0.0228)	-0.294 (0.0493)	-0.0581 (0.0182)	-0.0628 (0.0514)	-0.0868 (0.0187)	-0.168 (0.0497)
Calories per capita squared * 10^{-3}	0.0354 (0.00430)	0.0523 (0.00949)	-0.00725 (0.00381)	0.00754 (0.0107)	0.0132 (0.00389)	0.0286 (0.0102)
R^2	0.808	0.814	0.798	0.686	0.785	0.619
F or χ^2	197	72.0	109	22.8	1840	461
# Countries	49	49	49	49	49	49
# Observations	566	243	566	243	566	243

Notes: Standard errors are in parentheses. For OLS estimates, White's heteroskedasticity consistent standard errors are reported. Each regression also includes yearly dummies for 1972, 1975, 1977, 1980, 1982, 1985, 1987, 1990, 1992, 1995, 1997, and 2000. All 1975 data was missing in the regressions with child mortality as the dependent variable, so the dummy for year 1975 was not included. Child mortality rate is the under-five mortality rate. The R^2 value for the OLS regression is a measure of the goodness of fit in the ordinary regression equation. This is different from the R^2 value for the fixed and random effect estimators, where the R^2 value reported is the R^2 within value. The R^2 from the fixed-effect estimator is the same as the OLS R^2, but the R^2 from the random-effect estimator is not. F statistics are listed for OLS and fixed effect estimates. χ^2 statistics are listed for random effect estimates. Biomass fuels are defined by the IEA as solid biomass and animal products (including wood, vegetal waste, ethanol, animal materials/wastes, and sulfite lytes), gas/liquids from biomass, industrial waste, municipal waste, and hospital waste. Sulfite lytes are also known as "black liquor" and are alkaline spent liquor from the digesters in the production of sulfate or soda pulp during the manufacture of paper. The energy is derived from the lignin removed from the wood pulp. For sources, see Appendix 3.

Table 5. *The effect of the percent of biomass fuel use on life expectancy in non-OECD countries; OLS and fixed effect estimates, 1972-2000.*

Dependent variable:	(1) Life expectancy	(2) Male life expectancy	(3) Female life expectancy	(4) Life expectancy gap (F-M)	(5) Life expectancy	(6) Male life expectancy	(7) Female life expectancy	(8) Life expectancy gap (F-M)
Estimation Method:	OLS	OLS	OLS	OLS	Fixed	Fixed	Fixed	Fixed
Explanatory variables:								
Percent of biomass fuel use	-0.00239	-0.00294	-0.00181	0.00113	0.00211	0.00190	0.00232	0.000414
	(0.000426)	(0.000436)	(0.000432)	(0.000173)	(0.000549)	(0.000530)	(0.000585)	(0.000197)
Years of female education (2000)	2.20	1.92	2.50	0.578	-0.887	-0.812	-0.965	-0.153
	(0.319)	(0.319)	(0.325)	(0.0937)	(0.356)	(0.344)	(0.380)	(0.128)
Years of male education (2000)	-0.289	-0.0228	-0.568	-0.545	0.471	0.446	0.497	0.0511
	(0.346)	(0.351)	(0.346)	(0.0958)	(0.297)	(0.287)	(0.316)	(0.106)
Log of GDP per capita	2.78	2.44	3.14	0.701	1.43	1.02	1.86	0.836
	(0.575)	(0.566)	(0.600)	(0.192)	(0.474)	(0.458)	(0.505)	(0.170)
Urban % of population	-0.275	-0.0443	-0.00993	0.0344	0.0317	0.0366	0.0265	-0.0101
	(0.0157)	(0.0155)	(0.0161)	(0.00440)	(0.0379)	(0.0366)	(0.0404)	(0.0136)
Calories consumed per capita per day	0.0411	0.0366	0.0459	0.00929	0.00950	0.00899	0.0100	0.00104
	(0.00519)	(0.00495)	(0.00558)	(0.00188)	(0.00418)	(0.00404)	(0.00446)	(0.00150)
Calories per capita squared * 10^{-3}	-0.00703	-0.00606	-0.00804	-0.00199	-0.000873	-0.000868	-0.000877	-0.000009
	(0.000983)	(0.000941)	(0.00106)	(0.000362)	(0.000874)	(0.000845)	(0.000932)	(0.000313)
R^2	0.780	0.754	0.797	0.477	0.704	0.698	0.699	0.264
F	247	201	276	28.3	65.7	63.8	64.0	9.86
# Countries	49	49	49	49	49	49	49	49
# Observations	563	563	563	563	563	563	563	563

Notes: Standard errors are in parentheses. For OLS estimates, White's heteroskedasticity consistent standard errors are reported. Each regression also includes a constant term and yearly dummies for 1972, 1975, 1977, 1980, 1982, 1985, 1987, 1990, 1992, 1995, and 1997. All 1975 data was missing in the regressions with under-5 mortality as the dependent variable, so the dummy for year 1975 was not included. The R^2 value for the OLS regression is a measure of the goodness of fit in the ordinary regression equation. This is different from the R^2 value for the fixed-effect estimator, where the R^2 value reported is the R^2 within value. The R^2 from the fixed-effect estimator is the same as the OLS R^2. Biomass fuels are defined by the IEA as solid biomass and animal products, gas/liquids from biomass, industrial waste, and municipal waste. Biomass fuels are defined by the IEA are solid biomass and animal products (including wood, vegetal waste, ethanol, animal materials/wastes, and sulfite lytes), gas/liquids from biomass, industrial waste, municipal waste, and hospital waste. Sulfite lytes are also known as "black liquor" and are alkaline spent liquor from the digesters in the production of sulfate or soda pulp during the manufacture of paper. The energy is derived from the lignin removed from the wood pulp. For sources, see Appendix 3.

Table 6. *The effect of cooking with traditional biomass fuels on the probability of an infant and child dying in Pakistan*

	Cook primarily with traditional biomass fuels?	
	No	Yes
Infants who survived until age one	5654	14023
Infants who died before age one	663	1945
Probability of infant dying before age one	10.5%	12.2%
Children who survived until age 5	4504	10813
Children who died before age 5	634	1969
Probability of child dying before age 5	12.3%	18.2%

Notes: Data from the Pakistan Integrated Household Survey 1991. Sample of infants excludes infants born within one year of the survey, and the sample of children excludes children born within five years of the survey.

Table 7. *Descriptive statistics for explanatory variables in infant mortality sample*

Explanatory Variable	Mean	Standard deviation
Child variables		
Female child (dummy)	0.476	0.499
Year of child's birth	77.709	8.422
Parental variables		
Mother's age at time of birth	19.926	4.488
Mother's age at time of birth squared	417.173	200.267
Mother's highest completed grade of schooling	1.458	3.334
Father's highest completed grade of schooling	4.377	4.746
Experience	15.574	8.176
Experience squared	309.374	329.829
Household variables		
Traditional biomass is main cooking fuel (dummy)	0.704	0.457
Times firewood used in a typical day	2.06	1.670
Chimney exists (dummy)	0.232	0.422
Cooking occurs in open air or courtyard (dummy)	0.688	0.463
Open fire stove (dummy)	0.356	0.185
Fireplace (dummy)	0.659	0.474
Tripod (dummy)	0.032	0.177
Tandur Oven (dummy)	0.009	0.0959
Multiple Stoves (dummy)	0.264	0.441
Log of total monthly expenditures	8.298	0.743
Sanitation system (dummy)	0.665	0.472
Toilet (dummy)	0.671	0.470
Community variables		
Rural (dummy)	0.515	0.500
Price of rice	5.564	1.470
Price of masoor	20.004	3.613
Price of eggs	14.136	4.279
Sindh province (dummy)	0.281	0.449
NWFP province (dummy)	0.155	0.362
Balochistan province (dummy)	0.078	0.268

Notes: Sample means may differ in later discussion because sample sizes in regressions are slightly different. Data from the Pakistan Integrated Household Survey 1991.

Table 8. *The effect of traditional biomass fuel use on child mortality in Pakistan, Logit estimates.*

	(1)	(2)	(3)	(4)	(5)
Sample:	Entire	Entire	Entire	Entire	Rural
Child variables					
Female child (dummy)	-0.200	-0.241	-0.192	-0.230	-0.164
	(0.135)	(0.138)	(0.138)	(0.141)	(0.213)
Year of child's birth	-0.00207	0.00135	0.000131	0.00337	0.00649
	(0.00847)	(0.00859)	(0.00857)	(0.00856)	(0.0139)
Parental variables					
Mother's age at time of birth	-0.261	-0.370	-0.258	-0.358	-0.105
	(0.0631)	(0.0786)	(0.0633)	(0.0799)	(0.0875)
Mother's age at time of birth squared	0.00498	0.00717	0.00477	0.00674	0.000714
	(0.00144)	(0.00179)	(0.00145)	(0.00184)	(0.00214)
Mother's highest completed grade of schooling	-0.0963	-0.105	-0.0953	-0.104	-0.0842
	(0.0279)	(0.0279)	(0.0277)	(0.0276)	(0.0670)
Father's highest completed grade of schooling	-0.00499	0.00184	-0.00855	0.0132	-0.00164
	(0.0169)	(0.0229)	(0.0170)	(0.0226)	(0.0262)
Experience		0.0540		0.0502	
		(0.0279)		(0.0278)	
Experience squared		-0.000841		-0.000763	
		(0.000588)		(0.000582)	
Household variables					
Traditional biomass is main cooking fuel (dummy)	0.250	0.245			
	(0.171)	(0.177)			
Times firewood used in a typical day			0.0831	0.0816	0.124
			(0.0476)	(0.0497)	(0.0732)
Log of total monthly expenditures	-0.207		-0.210		-0.356
	(0.0938)		(0.0991)		(0.142)
Community variables					
Rural (dummy)	-0.0488	-0.134	-0.0174	-0.103	
	(0.189)	(0.187)	(0.184)	(0.178)	
Log Likelihood	973	883	946	857	452
# Observations	2408	2226	2330	2153	1035

Notes: Cluster standard errors for sample units are in parentheses. Absolute values of log likelihood reported. Each regression also includes the price of rice, masoor, and eggs and dummies for a sanitation system, toilet, Sindh province, NWFP province, and Balochistan province. Child mortality is death before age 5. Data from the Pakistan Integrated Household Survey 1991.

Table 9. *The effect of traditional biomass fuel use on infant mortality in Pakistan, Logit estimates.*

	(1)	(2)	(3)
Sample:	Entire	Entire	Rural
Child variables			
Female child (dummy)	-0.338	-0.326	-0.277
	(0.129)	(0.132)	(0.202)
Year of child's birth	0.0221	0.0238	0.0368
	(0.00725)	(0.00734)	(0.0118)
Parental variables			
Mother's age at time of birth	-0.235	-0.241	-0.138
	(0.0551)	(0.0559)	(0.0712)
Mother's age at time of birth squared	0.00455	0.00453	0.00237
	(0.00121)	(0.00123)	(0.00158)
Mother's highest completed grade of schooling	-0.0899	-0.0893	-0.0562
	(0.0260)	(0.0262)	(0.0580)
Father's highest completed grade of schooling	0.00210	0.00113	-0.000840
	(0.0157)	(0.0156)	(0.0215)
Household variables			
Traditional biomass is main cooking fuel (dummy)	0.117		
	(0.180)		
Times firewood used in a typical day		0.0401	0.0511
		(0.0468)	(0.0738)
Log of total monthly expenditures	-0.235	-0.244	-0.338
	(0.0893)	(0.0890)	(0.131)
Community variables			
Rural (dummy)	-0.00173	0.0117	
	(0.174)	(0.165)	
Log Likelihood	1036	1005	493
# Observations	2899	2806	1253

Notes: Cluster standard errors for sample units are in parentheses. Absolute values of log likelihood reported. Each regression also includes the price of rice, masoor, and eggs and dummies for a sanitation system, toilet, Sindh province, NWFP province, and Balochistan province. Infant mortality is death before the age of one. Data from the Pakistan Integrated Household Survey 1991.

Table 10. *Impact on life expectancy of eliminating biomass fuel use vs. HIV/AIDS epidemic in countries with the highest HIV/AIDS prevalence.*

Country:	Percent of biomass fuel use	(1) Impact on life expectancy of eliminating biomass fuel use	(2) Impact on life expectancy of HIV/AIDS epidemic	(Column 1 minus 2) Difference in life expectancy impact
Rwanda	90.2	7.8	9.7	-1.8
Mali	88.8	7.7	2.6	5.1
Malawi	88.6	7.7	13.9	-6.2
Mozambique	88.3	7.7	11.1	-3.4
Benin	87.8	7.6	3.0	4.7
Central African Republic	87.4	7.6	10.9	-3.3
Haiti	76.4	6.6	5.8	0.9
Kenya	76.2	6.6	16.6	-10.0
Ghana	74.3	6.5	4.8	1.7
Cameroon	67.5	5.9	8.7	-2.8
Zambia	63.6	5.5	17.4	-11.9
Guinea-Bissau	56.4	4.9	2.3	2.6
Congo, Rep.	51.9	4.5	7.3	-2.8
Honduras	50.1	4.4	1.9	2.4
Togo	47.9	4.2	7.0	-2.9
Zimbabwe	34.8	3.0	25.7	-22.7
Brazil	27.9	2.4	0.5	1.9
Guyana	22.8	2.0	4.5	-2.5
Thailand	22.2	1.9	1.9	0.1
India	19.7	1.7	0.7	1.0
Dominican Republic	8.7	0.8	2.7	-2.0
South Africa	5.7	0.5	18.3	-17.8

Notes: Sample of countries is from those with the highest HIV/AIDS prevalence according to the UN Population Division and those with available biomass fuel data. Impact on life expectancy of HIV/AIDS epidemic is calculated by subtracting current life expectancy from projected life expectancy without HIV/AIDS. Life expectancy figures from the UN Population Division, *World Population Prospects: The 2000 Revision*, 2001. Percent Biomass Fuel Use is calculated from Table 4, *Energy Statistics Yearbook*, United Nations (1998). Percent biomass fuel use is defined as the percentage usage of fuelwood, charcoal, bagasse, animal, vegetal and other wastes out of total fuel use. The consumption of different types of biomass fuel (and total fuel) are standardized by conversion to thousand terajoules.

Appendix 1. *Data sources for macro analysis*

Variable Definition	Sources
Infant mortality rate: number of deaths before age one per 1,000 live births in a given year, annual	World Bank, *World Development Indicators*, 2002
Child mortality rate: probability that a newborn infant will die before reaching age five if subject to current age-specific mortality rates, measured as deaths per 1,000 live births, annual	World Bank, *World Development Indicators*, 2002
Life expectancy (Both sexes, Male, and Female): number of years a newborn infant would live if subject to current age-specific mortality rates, annual	World Bank, *World Development Indicators*, 2002
Percent of biomass energy consumption out of total energy consumption:	
(a) 1998 cross-sectional data	(a) United Nations, *Energy Statistics Yearbook 1998*
(b) 1971-2000 panel data, annual	(b) International Energy Agency, *Energy Balances of non-OECD Countries 2002*, Online database
Years of education completed by individuals over age 15, by sex, five-year periods, 1970-2000	Barro and Lee (2000) education data set, Updated April 2000
Real GDP per capita, purchasing power parity, annual	Heston, Summers, and Aten, *Penn World Table Version 6.1*, October 2002
Urban percent of population, annual	World Bank, *World Development Indicators*, 2002
Percent of children age one immunized for dpt, 1980-1999, annual	World Bank, *World Development Indicators*, 2002
Calories consumed per capita per day, annual	Food and Agriculture Organization of the United Nations, FAOSTAT statistics database, 2002.
Mean rainfall in capital city in centimeters, 1990	Bloom et al. (2002) data set
Standard deviation of rainfall in capital city at monthly intervals from yearly mean in centimeters, 1990	Bloom et al. (2002) data set
Mean temperature in capital city in degrees Celsius, 1990	Bloom et al. (2002) data set
Standard deviation of temperature in capital city at 3-month intervals from the yearly mean in degrees Celsius, 1990	Bloom et al. (2002) data set