Investigating the Relationship between Income, Health and Biomass Consumption: A Panel Data Analysis

Oparinde, Adewale

University of Cambridge

31 July 2010

Investigating the Relationship between Income, Health and Biomass Consumption: A Panel Data Analysis

Adewale Oparinde[1]

[1]Department of Land Economy, University of Cambridge.

ABSTRACT

The inverted-U shaped relationship between environment and economic growth has been well established in the environmental Kuznets curve (EKC) literature for several local air pollutants, such as suspended particulate matter. Very few studies, however, tested the EKC relationship for biomass consumption. About 2.5 billion people in developing nations depend on biomass fuels for household cooking and lighting. Most of these people are located in the rural areas and have lower income levels than national averages. Biomass fuels, although more easily accessible, are less efficient than other fuel types, and they cause adverse health impacts due to indoor air pollution. Within the households that use biomass fuels, women and children bear most of the health costs. This study employs panel data from 132 countries, from 1971 to 2004, in order to fulfil two aims: First, to test whether or not there is an EKC type relationship between biomass consumption and economic growth. Second, to investigate the impact of biomass consumption on household health, measured by life expectancy and infant mortality. We find a true EKC for biomass consumption with the turning – point occurring at a very low level of income per capita (US $119). After the turning point, it is hypothesised that countries switch to more efficient and less polluting fuel, and hence climb up on the 'energy ladder'.

Further panel data analysis reveals that biomass consumption (negatively) and income level (positively) affects the health status of a country. The results of the cross-sectional data analysis reveal whether or not an EKC type relationship can be found depends on the year of data and econometrics technique utilised. We find that panel data fixed effect estimation method is superior to the cross-sectional data ordinary least square method in establishing the EKC type relationship for biomass consumption. The results of the panel data analysis reported in this study reveal that developing countries cannot wait for economic growth to take place to reach the turning point as a policy solution. The problem of biomass consumption should be tackled at early stages of economic growth since the health benefits brought about by economic growth can be negated by adverse health effect of biomass use. We therefore recommend that developing countries should focus on economic policies on an energy limb to alternative sources of energy, such as solar thermal energy. Such policies would not only eliminate the negative impacts of biomass consumption on health, but also enable prevention of reliance on intermediate fuels such as fossil fuel, which have been found leading to global climate change.

1. Introduction

Almost 82% of the global population live in developing countries and this figure is expected to increase to 86% by 2050 (United Nations, 2006). Information on energy consumption levels, patterns, and the types of energy used in developing countries are therefore crucial for consideration when designing policies for mitigation of climate change, reduction of poverty and improvement of health status. The primary energy mix in these regions, as well as in developed countries, ranges from biomass, coal, fossil fuel, hydroelectric to nuclear power (IEA, 2004). The International Energy Agency (IEA), however, has recently reported that about 2.5 billion people located in developing countries depend on biomass fuels (IEA, 2006). Majority of these people are located in the rural areas and have lower income levels than national averages.

Biomass is defined as organic matter of plant or animal origin used for energy. Biomass fuels are regarded as combustible renewables and wastes (e.g., vegetable material and waste, black liquor, landfill gas, alcohol, bio-additives)[1], traditional fuels (e.g., fuel wood, bagasse, charcoal)[2] or wood products[3]. The implications of biomass fuel use on climate change, deforestation, and human health (WHO, 2002) has prompted several studies on the energy use patterns in developing countries, and the links between biomass fuel use, income and health at both micro and macro levels (e.g., Panayotou, 1993; de Almeida and de Oliveira, 1995; Judson *et. al.* 1999; Foster *et. al.*2000; Barbier and Burgess, 2001; Victor and Victor, 2002; Jiang and O'Neill, 2003). Further, a large number of studies have tested for the existence of an inverted-U shape relationship between economic growth and environmental pollution (e.g. Selden and Song, 1994; Panayotou 1995, Arrow et. al.1995; Stern et. al., 1996; Cole et. al. 1997; Bhattarai and Hammig 2001). This inverted-U shape relationship implies that pollution rises as per capita income rises at early stages of economic growth, until a turning point level of income, after which pollution decreases as income per capita rises. This relationship has been referred to as environmental Kuznets curve (EKC) hypothesis in the literature (Figure 3).

[1] International Energy Agency - Biomass Energy Data Definition
[2] United Nations - Biomass Energy Data Definition
[3] Food and Agricultural Organisation – Biomass Energy Data Definition

This paper investigates the relationship between environmental pollution, in the form of biomass consumption, and economic growth using panel data estimation technique for a cross section of 132 countries (please see Appendix I for a list of countries), covering 34 years, from 1971 to 2004. The aims of this study are twofold. Firstly, to test whether or not there is an EKC type relationship between biomass consumption and economic growth (expressed in terms of income per capita) and to establish the tuning point. Secondly, to investigate the relationship between biomass consumption, income and health.

Likewise, the contribution of this paper to the literature is twofold. On one hand, even though several studies have investigated the relationship between income and pollution levels from energy consumption, most of these have been at a micro level. Further, to our knowledge no EKC study has so far focused specifically on biomass consumption. On the other hand, even though there have been a handful of studies investigating the relationship between income, pollution and health, none has specifically focused on the impact of biomass consumption on health in the respect of these combined links.

The rest of the paper is organised as follows. The following chapter presents a review of biomass sources, energy consumption pattern and link with health, income and poverty. Chapter 3 presents the economic theory behind the EKC and a review of the literature on EKC, as well as on pollution and health. Chapter 4 presents the data sources, analytical framework and variables included in the models. Chapter 5 explains the econometric methodology. Chapter 6 presents and critically discusses the results of the econometric estimations. The final chapter concludes with policy implications and recommendations for future research.

2. Background

2.1 Energy: Sources and Consumption Pattern in Developing Countries

Both renewable (e.g. energy from traditional fuel, bio-gas, wind energy, solar thermal) and nonrenewable energy types are used in households of developing countries but at varying degrees depending on access, efficiency and income level (IEA, 2004). A significant amount of time is spent on fuel gathering for cooking by women and children in these countries. Biomass is mainly used for cooking, lighting, and heating, and constitutes about 7% of the global primary energy demand (IEA, 2006). Empirical evidences have shown that biomass fuel forms the highest percentage in household energy portfolio in some developing countries. For example, Heltberg (2003) reported that only 16% of households in Brazil use firewood in cooking, while in Ghana 96% use firewood (rural areas) and charcoal (urban areas) for cooking. In India, where about 72% lives in rural areas, household energy consumption portfolio in 1995 is made up of 77% biomass use, 18% liquid fuel, and 5% electricity. Also in China, about 200 million tons of oil equivalent (toe) of biomass was consumed in 1990. In the Republic of Korea, however, a transition is evident in as only 5% of the household energy demand is biomass (Dzioubinski and Chipman, 1999).

This transition in energy consumption pattern in some developing countries, i.e., switching from dirty traditional fuels to cleaner modern energy (e.g. electricity), has been termed 'energy ladder', 'fuel switching' or 'fuel substitution' depending on the author (Heltberg, 2003). The 'energy ladder' model describes a stepwise use of energy type which changes as the household income level increases. The ladder shows a three-step route of movement in fuel switching from initial dependence on less efficient traditional biomass fuels and primitive technologies (Elias and Victor, 2005) to transition fuel, such as kerosene, which is more efficient than biomass, and finally to highly efficient modern energy, such as electricity, bottled gas or LPG (Leach, 1992).

Leach (1992) found that energy transition is common in the urban areas of the developing countries and it is strongly dependent on urban population and household income. In reality, unlike in figure 1, there is no clear distinction between the ladders of energy transition in developing countries. This is because many households have been found to have a portfolio of multiple types of energy, e.g., wood for cooking and heating, and kerosene and electricity for lighting (Masera et. al. 2000; Davis, 1998; Saatkamp, 2000). Generally, *'…transition is most commonly defined as a decrease in the proportion of household energy derived from biomass…''* (Jiang and O'Neill 2004). However, about half of the global population is still dependent on the biomass fuels (ladder 1), which have low efficiency and negative impacts on household health and hence income (WHO, 2000).

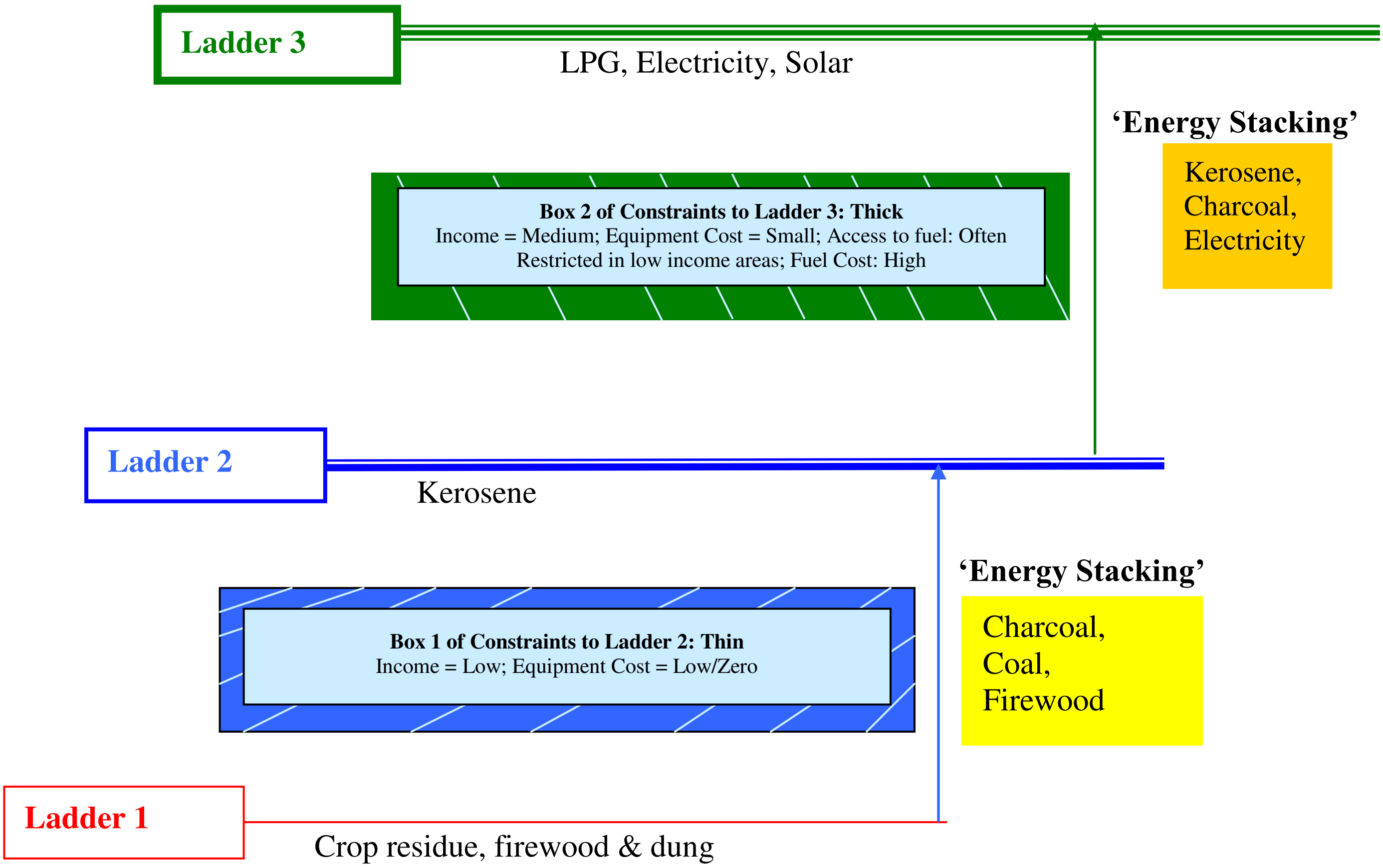


Figure 1: 'Energy Ladder' Model

2.2 Health, Indoor Air Pollution and Poverty

One of the greatest concerns about biomass consumption is the indoor air pollution, which is found to cause serious health problems in developing countries. Smoke from incomplete combustion during biomass burning as shown in Appendix II contains a large number of pollutants such as CO and Suspended Particulate Matter (SPM), which have associated public health risks. The effect is greatly observed in rural dwellers of developing countries but an increasing trend is also observed for the urban poor (WHO, 2000). Exposure to indoor air pollution from biomass has a strong association with several diseases. The link between indoor air pollution and infant mortality dates back to 1960s when studies carried out in Nigeria (Sofoluwe, 1968), and Papua New Guinea (Anderson, 1978) threw some light into the causal relationships. More recent studies have established the evidence of this causal link (e.g. Bruce et. al., 2000).

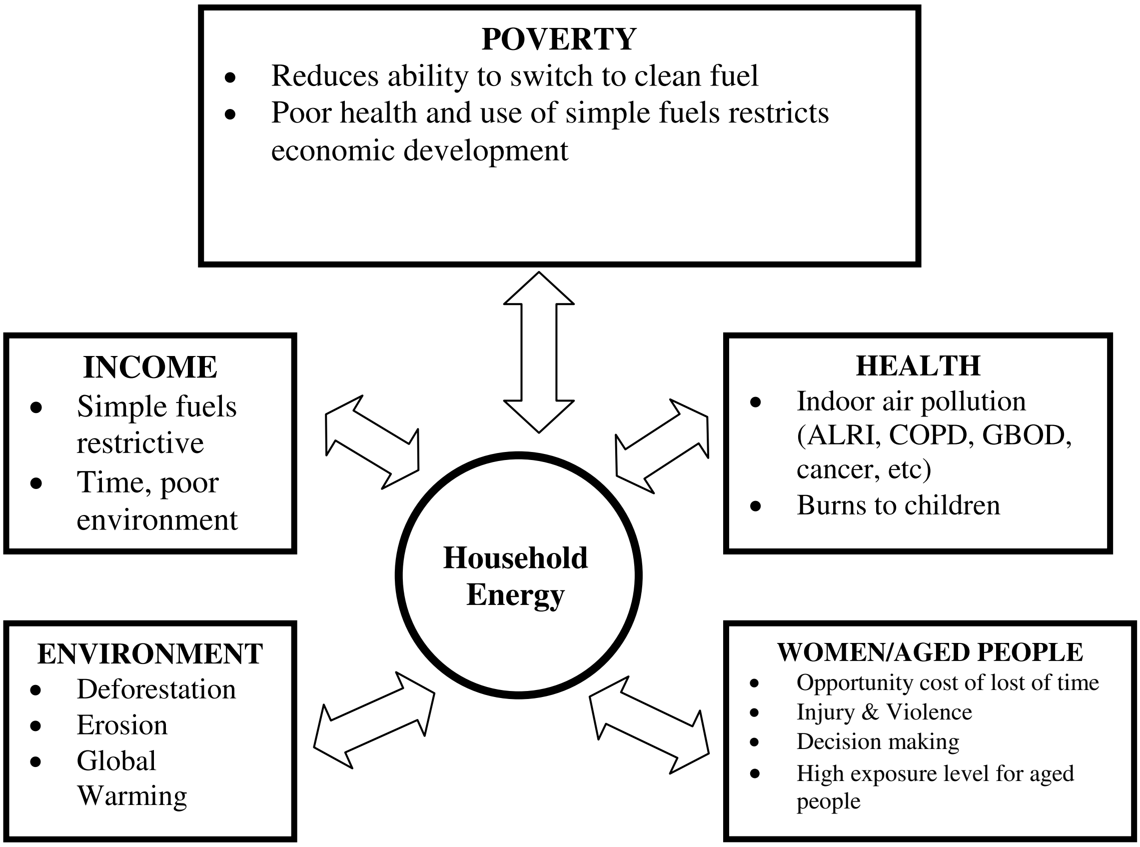
Ezzati et. al. (2000; 2002) recorded particulate matters (PM_{10}) concentrations of up to 50,000 $\mu g/m^3$ from immediate vicinity of fire from cookstove which is greater than the US EPA[4] daily average concentration of PM_{10} by about 333 folds. McCracken and Smith, 1998 observed variation in emission concentration of PM_{10} from Indian, South African and Guatemalan cookstoves which shows that exposure level could vary across homes, regions and countries. These pollutants cause acute respiratory diseases in women, which lead to increasing risk of lung cancer, as well as infant mortality. Several studies have reported the relationship between smoke from biomass use and general acute respiratory illness (e.g. Smith and Mehta 2000; Schirnding et. al., 2002), and as well as between biomass use and death in the first week of life in children (WHO, 2000). Fine particles (< 10 microns) penetrate down into the lungs causing acute lower respiratory infection (ALRI) and chronic obstructive pulmonary disease (COPD). ALRI and COPD from solid fuel use accounted for about 1 million childhood deaths globally in 2000 (Smith et. al., 2002) and 41,000 deaths in Africa in 2000 respectively.

[4] US EPA: United States Environmental Protection Agency

56% of all indoor air pollution-attributable deaths occur in children and women because in many developing countries women are responsible for household cooking and children are often carried on their back (*WHO Indoor Air Thematic Briefing 2*). Over 10 million deaths of children under the age of five occur yearly, and 99% of this occurs in developing countries (Rehfuess, 2006). The indoor air pollution as a risk factor constitutes an estimated amount of 2.7% to global burden of disease (GOBD) (WHO, 2005). Low income levels poverty, power relation within household (Viswanathan and Kumar, 2005), fuel availability and uncertainty, and technological know-how (Clay, 2002) have been identified as the most important factor limiting fuel switching potential in developing countries (also see figure 2).

Income has been perceived as the main determinants of economic growth due to its inverted-U relationship with the environment and positive relationship with health. It is however important to note that the negative effect of pollution on health at lower income levels can erase any economic growth benefits from income by reducing the productivity of the population (in the form of household income), and thus could make the population return to less efficient energy sources, such as firewood. We therefore argue that economic growth policies with little or no consideration for environmental quality at initial phases of economic growth constitute a poverty trap. Economic development policies at lower income levels are necessary to capture the gains brought to health from increasing income instead of waiting for the turning point to be reached. In order to support this point, we investigate the effect of biomass consumption on population health.

Figure 2: Income, Health, and Biomass Links[5]



Source: (WHO, 2000)

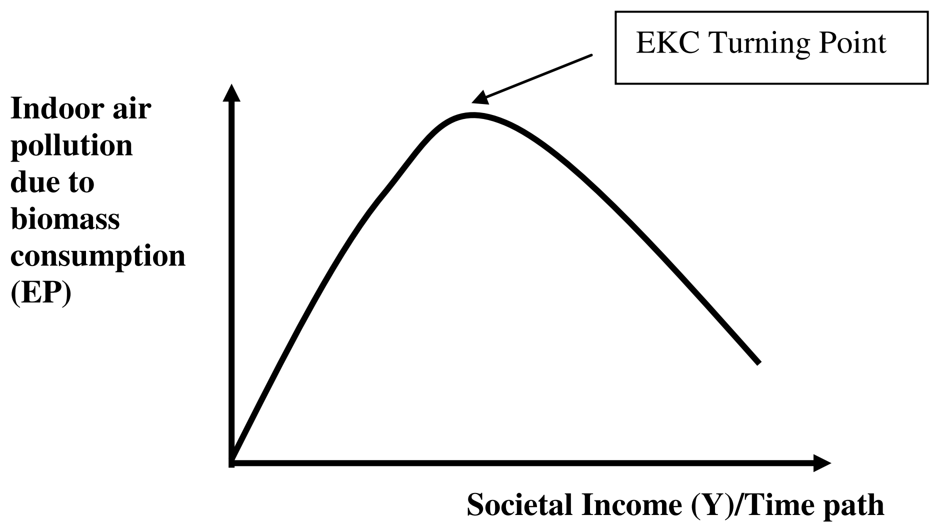
[5] Details can be found in WHO/HDE/HID/02.10., 2000. Please also see the reference.

3. Literature Review: Theory and Application of the EKC

3.1 Theory

The inverted-U relationship between environment and economic growth initially described by Beckerman (1972) and Simon (1977) could be defined for biomass consumption as a relationship in which people's willingness to pay (WTP) for efficient fuel decreases (de Bruyn, 2000) initially as income rises until enough wealth has been generated (Neumayer, 2004) for a turning to occur (figure 3).

Figure 3: A Conventional EKC

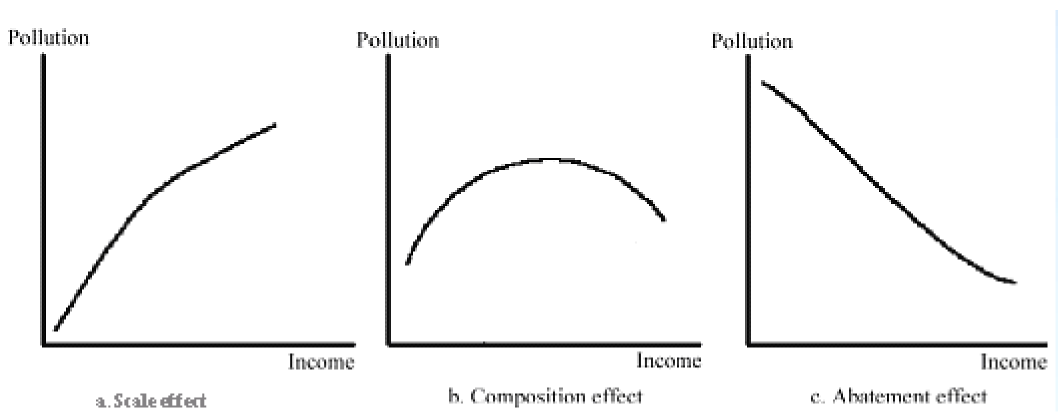


Victor and Victor (2002) reported that per capita biomass consumption has increased in the United States until 1830 and later the share of traditional biomass in primary energy consumption decreased with increasing economic growth. This illustrates the EKC hypothesis, which according to Barbier (1997) has controversial evidences and will be subjected to continuous verification through the use of different analytical methodologies. Recently, Jiang and O'Neill (2003) found that more than 70% of the total fuel use among China's rural population is based on biomass for heating and cooking.

In Brazil, only the wealthiest households use more efficient liquid fuels as their major fuel, while fuelwood accounts for almost all energy at the lowest income levels (de Almeida and de Oliveira, 1995). The EKC relationship although initially investigated for a policy trade off by Grossman and Krueger (1991) has been explained based on basic demand and supply theory by Antle and Heidebrink (1995). Their theoretical model shows that during the early phases of economic growth, resource depletion grows with economy until income grows to a point and the demand for environmental quality improvement increases leading to a development path (Yandle et. al., 2004). Panayotou (1997), however argued that the level of environmental quality resulting depend on the rate at which each level of economic growth is reached and therefore it is incomplete to assume that same level of environmental quality results at each level of income as taken in the above model. Generally, Panayotou identified three effects of economic activity determining the resulting environmental outcome as follows (also see figure 4).

i. **Scale Effect:** This can be explained to mean income per unit of area i.e. the level or scale of economic activity. Other factors remaining constant, the higher the scale of economic activity the higher will be the pressure on environmental resources and therefore we expect the scale effect of income to be a monotonically increasing function on environmental variable.

Figure 4: The Effect of Income on Environmental Quality



Source: Panayotou, 2003
http://www.unece.org/ead/pub/032/032_c2.pdf.

ii. **Composition or Structure of Economic Activity:** The content of an economy is an important factor for the environmental outcome. The sectors making up an economy determines the amount of pollution in a system. A country made up of agricultural, manufacturing and mining sectors will be more pollution-intensive than those made up of service sectors. An example of the former is the United Kingdom and that of latter could be China. However, as income increases the economic structure also changes and we could expect China likely to move from primary sector to service sector as its economy improves. This means that other factors held constant the composition effect will result in an initial shift from agriculture to manufacturing sector at early stages of economic growth and a shift from manufacturing to service sector at peak income. Thus a non-monotonic or inverted-U relationship between income and environment is expected.

iii. **Income Effect on Abatement Effort or 'Pure' Income Effects:** Panayotou (1997) also explains the pollution abatement effort to be influenced by demand and supply which is driven by income. In his words *'On the demand side, at low income levels, people are more concerned with food…and less concerned with environmental quality…At higher income levels people begin to demand for higher levels of environmental quality''*. Therefore, the pure income effects result in a monotonically decreasing relationship between income and environment.

We recognize these effects of income on environment but this thesis only takes an initial step of estimating the EKC model in order to understand the income-biomass consumption relationship (which has not been studied in the literature) and do not consider this as the end-point according to Panayotou (1997).

However, the EKC hypothesis was given a tremendous attention in the 1990s. Many empirical studies using cross-country and household level data have been done in order to test this hypothesis. Tables 1 and 2 summarize EKC studies on several local pollutants relevant to this study and the turning-point incomes obtained.

3.2 Review of EKC Macro Analyses

Most EKC studies conducted in 1990s are macro analysis using cross-country panel data. Several of these were conducted on air pollution and deforestation.

Air Pollution

Even though there are currently no macro level EKC studies on biomass consumption, there are several of such studies on the emission of local air pollutants such as SPM, CO, SO_2, methane and NOx. Grossman and Krueger (1991) showed an inverted U-shaped relationship for SO_2 in their investigation of the likely environmental impacts of North American Free Trade Agreement. Cole et. al., (1997) investigated the income-environment relationship for several air pollutants with local short-term impact, employing generalized least squares (GLS) fixed effect estimation technique. The results from their study show that EKC turning points for all pollutants estimated by the quadratic function ranges from \$5,700 for SO_2 to \$15,100 for NO_2 (1985 US Dollars) per capita while that for SPM falls in the middle. These turning-points for local pollutants are consistent with estimates from other studies. Grossman and Krueger, (1995) found a true EKC (an inverted-U shape) with a peak at \$6,151 for SPM using a similar estimation technique (GLS random effect), whereas Cole et. al. (1997) found this turning point to be \$8,100. Shafik and Bandyopadhyay (1992) also found a true EKC for SPM by using Ordinary Least Squares (OLS) fixed effect estimation method. They reported that the point of improvement starts at income level of \$3,280.

These results reveal that similar methods may yield estimates that are significantly different. The differences can be attributed to several factors including whether emissions per capita or per capita concentrations is used as pollution indicator; countries included in the panel dataset, years of data used, and non-income explanatory variables included in the regression models (Stern et. al. 1996). For instance, Selden and Song (1994) used urban air quality data (contrary to aggregate emission data used by Grossman and Krueger (1991)) and found different turning-points for SO_2 when different econometrics techniques were employed. Their random effect estimation yielded \$10,681 (1985 US dollars), while fixed effect estimate is close to this figure (\$8,916), whereas the cross-sectional estimate is very far ($668). This result is explained by Stern et. al. (1996) to be due to the presence of heteroskedasticity and thus OLS estimation being biased.

Deforestation

Statistically significant EKCs were found for 64 developing countries in Latin America and Africa for deforestation (Cropper and Griffiths, 1994). Panayotou (1995) employed 1980s data from 41 countries and found a lower turning point of $800 (1985 US dollars) per capita for deforestation compared to estimates for SO2 as discussed above. Bhattarai and Hammig (2001) also found a true EKC relationship for deforestation using data from 66 countries. Evidence of a turning point of $8,700 found for expansion of agricultural land use as indicator of environmental pressure on forests in tropical countries by Barbier and Burgess (2001) substantiates the findings of Bhattarai and Hammig (2001). On the same note, Ehrhardt-Martinez et. al. (2002) also established a substantial evidence of inverted U-shaped relationship for deforestation in 74 poor countries in Africa, Asia and Latin America. These evidences are contrary to the conclusion of Arrow et. al. (1995) that a true EKC is not possible for natural resource depletion.

3.3 Review of EKC Micro Analysis/Household Level Studies

A household level study is believed to capture important factors, such as spatial intensities, demographics, and household expenditure to name a few, which affect household energy consumption. These advantages of micro level studies have led to increasing use of household level micro-data and country-level data (e.g. Lenzen et. al., 2006; Aldy, 2005; Millimet et. al., 2003). Due to availability of data, several micro analyses have been conducted on developed countries.

Plassmann and Khanna (2003) employed 1990 data for the United States and a multivariate Poisson-lognormal model to estimate the income level at which households are willing to reduce their exposure to pollutants associated with respiratory health effects. They found an inverted U-shaped relationship between household income and PM_{10} with a turning point of $20,000. However, very few micro level studies related to biomass consumption have been conducted in developing countries. Viswanathan and Kumar (2005) studied the household level fuel use pattern over two decades using data from16 states of India, in order to understand the factors behind the energy transition process. Although they did not utilise an econometric model, the simple method of graphical representation of trend in energy use by income groups shows that at country level a switch to cleaner energy, such as Kerosene, is slow among the rural households as their expenditure share of cleaner fuel only marginally increased over ten years while that of urban households doubled. This is an indication that richer households are predominant in urban areas as economy may grow faster than in the rural area and thus high income households have a higher energy switching potential than a poor household which is consistent with the EKC hypothesis.

Foster et. al. (2000) tested the existence of energy transition process with a model of household energy utility as a function of net energy consumption[6] and efficiency factor.

[6] Net energy consumption is defined in the paper as a product of gross energy consumption and efficiency factor of the fuel

In their study, cross section data from a household level income and expenditure survey[7] in Guatemala was utilised and the efficiency factor of electricity was used as a reference point for other fuels (kerosene, firewood, battery, etc). In order to measure the net energy consumed according to household income, they classified ten per capita income deciles. They found that household gross energy consumption rises steadily with income and peaks at about fifth income decile where an average household spends US $229 per capita. This turning point income estimate was confirmed in their paper by also utilizing regression models and their result shows a similar turning point-income (US $205) for household energy consumption.

This review of the EKC literature shows that several indicators of environmental degradation have been used in the empirical investigations. Cole et. al. (1997) examined the EKC relationship for several pollutants including energy consumption, similarly to Torras and Boyce (1998) and Stern et. al. (1996). The most important feature common to all of these studies is that majority used panel data, similarly to this paper.

[7] They also included other dummy variables such as household geographical locations, and non-income characteristics like demographics, education and employment, and access to various energy sources including electricity in their regression models.

Table 1: Survey of Macro Level Analysis of EKC for Various Local Air Pollutants

Authors	Year	Pollutant (s) (Environmental Indicator)	Other Dependent Variable(s)	Economic Growth Indicator	Other Explanatory Variables	Estimation Technique	Data Type	Data Source	Countries	Period	EKC turning point
Grossman and Krueger	1991	SO_2	_	GDP (PPP)	Population density, dummies for locations, etc	GLS Random Effect	Aggregate emission data		Cities and not country-level data were used and 32 countries were considered	1977, 1982 and 1988	$ 4772 (1990 US Dollars) lower point
Shafik and Banyopadhyay	1992	SO_2/SPM/ Deforestation	Lack of Safe water, Lack of urban sanitation, etc	GDP (PPP)	Location dummies	OLS fixed effect	Aggregate emission data	World Bank database	Several countries different for each variable but ranging from 44 – 90 countries	Several time periods ranging from 1960 - 1986	$3, 670/ $3, 280/ flat shape (no EKC)
Panayoutou	1993	SO_2/ SPM/NOx	_	GDP (market exchange rate)	_	OLS	Fuel use data (emissions)		55 countries (both developed and developing)	1987 - 1988	$3,137/$4,500/ $5,500
Selden and Song	1994	SO_2/ SPM/NOx	_	GDP (PPP)	Population density	GLS (random and fixed effects), OLS	emission data	GEMS, PMWT	8 developing countries and 22 OECD Countries	1979 - 1987	$10, 300/$10, 300/ $11,200
Grossman and Krueger	1995	SO_2/ SPM	_	GDP (PPP)	Lagged income	GLS (random effect)	concentrations				$4,100 – 13,000 / $6, 200
Cole et. al.	1997	SO_2/SPM	_	GDP (PPP)	Country dummies	GLS (fixed effects) quadratic form		OECD	11 OECD countries		$ 5,700/ $8,100
Torras and Boyce	1998	SO_2/SPM	_	GDP (PPP)	Income inequality	OLS	concentrations				Flat shape curve
Gangadharan and Valenzuela	2001	Commercial energy use	LIFE, INFM	GDP (PPP)	Population density, urban population	OLS, 2 stage least square		World Bank Database	51 developing and developed countries (22 OECD)	1998	$6,043
This Thesis	2007	Biomass fuel Consumption	LIFE, INFM	GDP (PPP)	urban population, education	Panel Data (OLS fixed effect), OLS		World Bank, UN	136 developing and developed countries	1971 - 2004	

GEMS: Global Environmental Monitoring System; PMWT: Penn Mark IV World Tables; LIFE: Life Expectancy; INFM: Infant mortality rate; OLS: Ordinary Least Square; GLS: Generalized Least Square; PPP: Purchasing Power Parity; SPM: Suspended Particulate Matter, UN: United Nations Database

Table 2: Survey of empirical studies that used household level micro-data

Author(s)	Year	Type of Data	Country	Method	Environmental Indicator	Independent Variables	Turning Point Income
Foster et. al.	2000	ENIGFAM[8] household energy consumption and expenditure data between April 1998 – March 1999	Guatemala	OLS (logarithmic)	Gross energy consumption in Kilowatts	Household income, location dummies, non-income household characteristic, access to energy sources	A peak consumption obtained at around fifth decile (US $205).
Plassmann and Khanna	2003	Used disaggregated count data (at census tract level) of smallest geographic unit possible (1990)	United States	Multivariate Poisson-lognormal model	SPM, CO and ground level ozone (Number of days in a year during which the ambient concentration of a pollutant exceeds the NAAQS)[9]	Household income	PM10 ($20, 000), no such clear and significant relationship for CO and Ozone.
Viswanathan and Kumar	2005	Household survey data on cooking fuel consumption between 1983 – 2000 at national level (rural and urban areas) and across states	India	No model specified	Fuel consumption	Household energy expenditure	–

[8] Encuesta Nacional de Ingresos y Gastos Familiares
[9] National Ambient Air Quality Standards (NAAQS) established by US Environmental Protection Agency.

3.4 Empirical Study on Income, Health and Biomass Consumption Link

Since 2000, EKC studies have changed focus as an increasing number of authors extended the model beyond environmental effects to include investigation of two stage effects between income, the environment and human health. Positive relationship between health and income has been well recognized and studied in international development (Bloom and Canning, 2000). It is believed that higher levels of income lead to improvements in health status. Mostly, studies on this relationship have employed income variable measured as income levels over a number of years, income change over time or duration of poverty experience as categorized by Benzeval et. al. (2000). It has been found in some of the cross-sectional studies that income loss overtime results in poorer health than income gain overtime (Hirdes et. al., 1986; Duncan, 1996). A survey by Benzeval et. al. (2000) provides evidences that poverty is a significant threat to human health. Smith and Zick (1994) found that people living on low income for long time period have worse health outcome than those who infrequently experience poverty.

However, the relationship might also work in another way: as the economy grows, environmental pollution increases leading to lost workdays due to illness. The adverse health effect of biomass use should lead to increased mortality especially in infants, children and their mothers. In a cross country study, Yeh (2004) shows that as use of biomass fuel increases there is an increasing trend of average infant mortality rate and child mortality. As a result, the health benefits obtained from increased income could be negated by the social health cost incurred from pollution. This hypothesis was found to be true in a cross-country analysis of developing countries by Gangadharan and Valenzuela (2001). In this study, the impact of commercial energy use and other environmental pollutants on life expectancy and infant mortality rate was investigated using OLS and two stage least square estimation techniques. Their results show a statistically significant negative effect of energy use on health. Although education was found to be insignificant in predicting life expectancy, other variables including income, immunization rates, physicians per population and urbanization were reported to be significant predictors of infant mortality and child mortality rates. This finding requires research and policy attention for various important reasons, e.g. the global burden of disease due to biomass consumption is significant (WHO, 2005). Also, a household livelihood depends greatly on health of the family members. *'Being ill as a result of indoor smoke or having to care for sick children reduces earnings and leads to additional expenses for health care and medication'* (Rehfuess, 2006) and this could lead to a kind of poverty vicious circle for biomass consumption.

We therefore extend our EKC study to investigate the impact of biomass use on health following Gangadharan and Valenzuela (2001), however we employ panel data fixed effects which is more efficient than cross section analysis. Briefly it will be worthwhile to mention that intuitively from Gangadharan and Valenzuela (2001)'s argument, it is observed that the negation of health gains at initial phases of economic growth could increase the height of the EKC, which will necessitate a higher income level as the turning point (Panayotou, 1997) if policy is not put in place at early phases of economic growth to capture the health gains *(this hypothesis was not tested in this study).*

4. Data and Analytical Framework

Data used in this study are obtained from several sources, including the United Nations Common Database (UNCDB), World Bank databases (WBKDSD), World Health Organisation Statistical Information System (WHOSIS), International Energy Agency (IEA) and Pen World Tables 6.2.

Biomass consumption data are obtained from IEA energy statistics. Data on the area of arable and permanent crops are collected from Food and Agricultural Organization (FAOSTAT). Six health variables, a population variable and a literacy rate variable are obtained from the WBKDSD. Per capita income measured in purchasing power parity (GDP) and population data are gathered from the Pen World Tables 6.2. Percentage of child death due to HIV/AIDS (HIV) and 2004 life expectancy of which data could not be obtained from the WBKDSD were taken from the WHOSIS.

Table 3 presents the variables, unit of measurement and their sources, while table 4 presents the number of countries included in each dataset used. Some variables do not have data spanning over several years and some countries lack key variables like GDP, thus we created 5 datasets. Panel datasets A and B contain data for 132 and 102 countries respectively covering years from 1971 to 2004 and the former presents the results of the EKC hypothesis test, while the latter reports the results of the health hypothesis test. Three cross-sectional datasets for years 1990, 2000 and 2004 were also created so as to allow comparison of results and verification of the claim by Stern et. al. (1996) that results depend on the year and sources of data included in a study, and estimation technique used. Countries included in all datasets are same as those in panel dataset A in which OECD and developing countries were well represented. A list of all countries included in panel dataset A is presented in Appendix I.

4.1 Dependent Variables

We conducted panel data analysis using biomass consumption (BIO), infant mortality rate (INFM) and life expectancy (LIFE) as endogenous variables. In this study, instead of using efficiency factor and gross energy consumption data as used by other authors (e.g. Foster *et. al.,* 2000), we utilised share of combustible renewables and wastes in the total primary energy flow which is a more specific-data. Life Expectancy variable does exhibit some shortcomings. Gangadharan and Valenzuela (2001) indicated that '*the causes of death in adults are much less likely to decrease with increases in per capita income since many adult deaths could be due to use of tobacco and alcohol and other related factors which rise with income'*. Although this shortcoming is recognised we could not obtain a time series data for healthy life expectancy which has been regarded as a better indicator. On the question of which health indicator is a true revelation of impact due to indoor air pollution, many studies have found statistically significant and negative income elasticity for infant mortality rate. Yeh (2004) shows that the negative effects of biomass fuel use on mortality are apparent in aggregate national indicators such as infant mortality. Therefore we consider infant mortality rate as having a good causal relationship with biomass consumption and it was chosen as a good alternative while we recognise the fact that impact of biomass use on health would have been well captured better by micro-level household data (Yeh, 2004).

4.2 Factors Determining Biomass Consumption

In the EKC literature, environmental quality has been shown to be explained by both income and non-income variables. Our study aims to test the EKC relationship for biomass consumption. As the IEA (2006) energy statistics shows that the majority of biomass consumption is still in the developing countries where there is low GDP per capita while cleaner fuel dominates only in households of developed world we expect a high level of biomass use at lower levels of income. In line with this, a shift to cleaner energy sources is expected to take place at very low level of income (i.e. the turning point). This negative association is expected since we believe that as income rises a poor, rural household will climb the energy ladder and thus reduce the amount of biomass fuel use. We therefore employ real GDP per capita, purchasing power parity (GDPC) as the proxy for economic growth. Non-income factors, such as income inequality, literacy rate, political rights and civil unrest, urbanization and population level of a country, have been found to have impacts on the level of environmental quality (e.g. see Gangadharan and Valenzuela, 2001; Torras and Boyce, 1998; Selden and Song, 1994; Cole et. al., 1997; Shafik and Banyopadhyay, 1992). In this analysis, we assume that urbanization (UPOP) should lead to a decrease in the biomass fuel use, and thus a negative association is expected. Also, education is seen as a factor that creates awareness about the bad effect of indoor air pollution and low efficiency associated with biomass fuel. Hence we expect that the education level of a country (EDUP) should be negatively correlated with biomass consumption. The results of correlation test between income per capita and education level shown in tables 6, 7 and 8 indicates that there is no risk of endogenity problem between the two variables in all models employed.

Population density is an important explanatory variable since a high density indicates more pressure on environmental resources. However, a tradeoff between urban population and population density became necessary in this study as there was a strong correlation between the two variables and thus the strict exogenity and 'no multicollinearity' assumptions of the fixed effect estimation and Ordinary Least Square (OLS) methods used in this study could be violated. This is contrary to the work of Gangadharan and Valenzuela (2001) which is surprising because they included both simultaneously in their estimation model.

Table 3: Variables and Sources

Variable Code	Description of the Variable, Sources and Units
GDPC	Real gross domestic product per capita in Constant Dollars, purchasing power parity (1996 Benchmark) - PENN WORLD TABLES 6.2
GDPC2	GDPC square
UPOP	Urban Population (% total) - WORLD BANK KEY DEVELOPMENT STATISTICS DATABASES
FPDN	Forestry Production (roundwood, million cubic metres) - United Nations Common Database (UNCDB) FAOSTAT
ALANDA	Area of arable and permanent crops (1000 hectares) per total land area - United Nations Common Database (UNCDB) FAOSTAT
EDUP	Gross enrollment rate in primary school (%), total - WORLD BANK KEY DEVELOPMENT STATISTICS DATABASES
BIO	Biomass consumption (Combustible Renewables and Waste) , Share of Total Primary Energy Supply, Million ton of oil equivalent (Mtoe) – IEA Energy Statistics
INFM	Infant mortality rate (per 1,000 live births) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)
LIFE	Life Expectancy at birth, total (years) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)
IMMU1	Child immunization rate (% of children ages 12-23 months) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)
DOCT	Physicians (per 1,000 people) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)
HIV	Deaths among children under five years of age due to HIV/AIDS (%) - WHO Statistical Information System (WHOSIS)
ASANF	Access to an improved water source, total (% of population) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)
AWATF	Access to improved sanitation facilities, total (% of population) - WORLD BANK HEALTH, NUTRITION AND POPULATION DATABASE (HNPD)

The level of biomass consumption in a country is also thought to be positively correlated with the extent of agricultural production since combustible renewables and wastes which make up biomass fuels, originate from agricultural production. For example, amount of biomass such as dung and firewood available in any country is assumed to depend on the amount of agricultural production. However, it should be noted that this assumption may not be universal as technology is an important factor that determines the area of land in agricultural production in a country. A comparison of FAOSTAT statistics on agricultural production in the United Kingdom and Brazil clearly shows this and the amount of forestry production could have been a suitable alternative but subjected to same issue. Contrarily, forest area in each country is considered a reasonable determinant of biomass production since this is not so much affected by other factors such as technology as discussed above. Unfortunately, we could not obtain data on this variable and we therefore normalized the area of arable and permanent crops by dividing it with the total area of land in each country and the variable is named ALANDA. This was then included as a predictor of biomass supply in all models. Table 5 lists the expected signs of the independent variables included in our models.

Table 4: Datasets and Number of Countries

Dataset	No of Countries
Panel Data A (1971 to 2004)	132
Panel Data B (1971 to 2004)	102
Cross-sectional Data, 1990	132
Cross-sectional Data, 2000	132
Cross-sectional Data, 2004	132

Table 5: Expected Signs of Explanatory Variables

	Dependent Variables		
Explanatory Variable	BIO	INFM	LIFE
GDP	-	-	+
GDP Square	-	n/a	n/a
UPOP	-	+/-	+/-
FPDN	+	n/a	n/a
ALAND	+	n/a	n/a
EDUP	-	-	+
BIO	n/a	+	-
IMMU1	n/a	-	+
DOCT	n/a	-	+
HIV	n/a	+	-
ASANF	n/a	-	+
AWATF	n/a	-	+

4.2 Factors Determining Life Expectancy and Infant Mortality

Bloom and Canning (2000) clearly shows that the positive correlation between economic growth and health has been well studied. It is expected that as income rises the health of a population should be getting better since food and drugs will gradually become affordable and thus mortality/morbidity rate should decrease. Environmental pollution, however, which results in the earlier phases of income growth, should have a negative effect on the health as we discussed in chapter 3. The increasing urban air pollution associated with economic growth is an indication of feedback effect on income through the impact of pollution on health. We could therefore expect infant mortality rate to increase with urban population on one hand (probably because there are ghettos in urban areas in developing countries where the conditions are even worse than in rural areas) and on the other hand decrease since urbanization will increase access to improved water and sanitation infrastructure.

Opposite of these relationship should occur in the case of life expectancy. Biomass use should be negatively associated with life expectancy and positively correlated with infant mortality. The health of a country is also thought to depend on other non-environmental factors, such as education level, access to health facilities, immunization rate, prevalence of infectious diseases, e.g., HIV/AIDS, and the number of doctors per population. For instance spread of a bacteria disease can be quicker and massive if the percentage of the total population having access to improved sanitation facilities (ASANF) is low. We therefore included percentage of total population with access to improved water source (AWATF), ASANF, number of physician per 1000 (DOCT), child immunization rate (IMMU1) and percentage of child death due to HIV/AIDS (HIV) in our models.

Table 6: Correlation between the estimators of biomass consumption (Panel data estimation A)

	GDPC	GDPC2	UPOP	ALANDA	EDUP
GDPC	1				
GDPC2	0.9435	1			
UPOP	0.2349	0.1597	1		
ALANDA	-0.1328	-0.0777	-0.154	1	
EDUP	0.0938	0.0833	0.3088	0.0986	

Table 7: Correlation between the estimators of population health (Panel data estimation B)

	GDP	UPOP	BIO	EDUP	IMMU1	DOCT
GDP	1					
UPOP	0.4013	1				
BIO	-0.2125	-0.3028	1			
EDUP	0.0156	0.0805	-0.0376	1		
IMMU1	0.4526	0.3213	-0.1814	-0.0524	1	
DOCT	0.4417	0.4664	-0.1553	0.0074	0.331	1

Table 8: Correlation between the estimators of population health (2004 Cross-sectional data estimation)

	EDUP	GDP	BIO	IMMU1	DOCT	HIV	ASANF	AWATF
EDUP	1							
GDP	0.1064	1						
BIO	0.1747	-0.1714	1					
IMMU1	0.2287	0.2761	-0.2585	1				
DOCT	0.0855	0.254	-0.0549	0.3051	1			
HIV	-0.0454	-0.1909	0.0097	-0.222	-0.222	1		
ASANF	0.168	0.351	-0.2529	0.115	0.245	-0.2286	1	
AWATF	0.256	0.377	-0.0993	0.2824	0.2824	-0.0862	0.3813	1
UPOP	-0.0063	0.3866	-0.1668	0.0917	0.0917	-0.3429	0.3177	0.192

5. Methodology

Generally, an EKC hypothesis is tested using a common method of fitting the data to the regression or a reduced form model:

$$\mathbf{EP_{it} = \Pi_{it} + \beta_1 Y_{it} + \beta_2 Y^2_{it} + \beta_3 Z_{it} + e_{it}} \qquad \textit{(I)}$$

EP represents environmental pressure (biomass consumption in this study); Y is the per capita income; subscript i stands for a country index; t stands for time index; Π is the intercept; β_i are the coefficients on explanatory variables; where Z_{it} stands for variables other than income that can influence EP; and e_{it} represents the normally distributed error.

Several studies have estimated model 1 above using different econometrics techniques (de Bruyn, 2000) ranging from pooled OLS to first-differenced equation (e.g. Cole et. al., 1997; Torras and Boyce, 1998). In a panel data set there are unobserved or fixed effects and idiosyncratic error term. In model II below the variable a_i is the fixed effect which captures all unobserved factors that do not change over time (t) but affect EP_{it} (Wooldridge, 2006).

$$\mathbf{EP_{it} = \Pi_{it} + \beta_1 Y_{it} + \beta_2 Y^2_{it} + \beta_3 Z_{it} + a_i + e_{it}} \qquad \textit{(II)}$$

This a_i refers to country heterogeneity in our panel data where e_{it}, represents the unobserved factors that change over time (idiosyncratic error) but affect EP_{it}. Many authors have removed this country-specific heterogeneity (a_i) using fixed and/or random effects estimation method. Cole et. al., (1997) used both methods in testing EKC hypothesis for air pollutants and energy use from transport. Critically following their step we conducted a Hausman specification test to ascertain which method estimates our panel data better. In both panel data estimation A and B discussed in chapter 4 the null hypothesis of no correlation between individual effects and independent variables was rejected. Therefore the EKC and health hypotheses were tested using fixed effects estimation technique.

5.1 PANEL DATA ESTIMATION MODEL

Panel data estimation technique is utilised in this study because it presents several advantages:

i. Some effects which can not be detected in cross-sectional or pure-time series data can be easily identified in panel data. For instance, if correlation between two explanatory variables is suspected cross-sectionally, panel data can be useful in verifying if same association exists within countries (Wooldridge, 2006).

ii. Panel data fixed effects estimation is more efficient than OLS (Stern et. al., 1996), and utilises more information (i.e. more data), and more degree of freedom.

iii. Panel data makes it easier to remove the covariance between the country heterogeneity and the explanatory variables.

On one hand, our interest is to see how biomass consumption is explained by certain factors, which could be said to be of two parts. First, time-varying observable factors such as level of economic growth (GDPC) determine the amount of pollution in a country. Also biomass use depends on other factors as explained earlier in section 4.2. Therefore biomass consumption is a function of level of economic growth (Y_i) and other factors that affect biomass use (Z_i) as shown in the following relationship.

$$\mathbf{EP_i = f\,(Y_i, Z_i)} \qquad \textit{(III)}$$

However, the second part consists of factors determining biomass use in a country that are unobservable but constant overtime (a_i). For instance the region where a country is located is constant every year but this determines the type of vegetation and agricultural practice in that country. Also the land area does not change and the amount of forest area in a country could also depend on this. The amount of agricultural wastes which are used as household cooking fuels in a country also depend on the area of land available for agricultural production. With these fixed effects, equation III becomes

$$\mathbf{EP_i = f\,(Y_i, Z_i, a_i)} \qquad \textit{(IV)}$$

We call this a '*fixed effect biomass consumption function' (FBF).* Taking this function we assume that the unobserved effects, a_i correlate with one or more of the explanatory variables (Y_i and Z_i) and therefore a fixed effect transformation is used to eliminate the a_i.

The FB function in equation (IV) can thus be expressed as follows for country i

$$\mathbf{BIO_i = f\,(GDPC_i, UPOP_i, ALANDA_i, EDUP_i, a_i)} \qquad \textit{(V)}$$

$$\mathbf{BIO_{it} = \beta_1 GDPC_{it} + \beta_2 GDPC^2_{it} + \beta_3 UPOP_{it} + \beta_4 ALANDA_{it} + \beta_5 EDUP_{it} + a_i + e_{it}} \qquad \textit{(VI)}$$

Biomass consumption (BIO_{it}) varies over time period t = 1, 2, ……, T; β_1 - β_5 are parameters to be estimated, a_i and e_{it} are constant and time-varying unobserved effects respectively while others are the independent variables as explained in section 4. With a fixed effect transformation, the average of equation VI over time for each country i becomes

$$\overline{\mathbf{BIO}}_{\mathbf{it}} = \beta_1\overline{\mathbf{GDPC}}_{\mathbf{it}} + \beta_2\overline{\mathbf{GDPC}^2}_{\mathbf{it}} + \beta_3\overline{\mathbf{UPOP}}_{\mathbf{it}} + \beta_4\overline{\mathbf{ALANDA}}_{\mathbf{it}} + \beta_5\overline{\mathbf{EDUP}}_{\mathbf{it}} + \mathbf{a}_{\mathbf{i}} + \overline{\mathbf{e}}_{\mathbf{it}} \qquad \textit{(VII)}$$

where $\overline{BIOit} = T^{-1} \sum_{t=1}^{T} BIOit$ ***(VIII)***

Subtracting equation VII from VI:

$$\overline{\mathbf{BIO}}_{\mathbf{it}} - \mathbf{BIO}_{\mathbf{it}} = \beta_1 (\mathbf{GDPC}_{\mathbf{it}} - \overline{\mathbf{GDPC}}_{\mathbf{it}}) + \beta_2 (\mathbf{GDPC}^2_{\mathbf{it}} - \overline{\mathbf{GDPC}^2}_{\mathbf{it}}) + \beta_3 (\mathbf{UPOP}_{\mathbf{it}} - \overline{\mathbf{UPOP}}_{\mathbf{it}}) + \beta_4 (\mathbf{ALANDA}_{\mathbf{it}} - \overline{\mathbf{ALANDA}}_{\mathbf{it}}) + \beta_5 (\mathbf{EDUP}_{\mathbf{it}} - \overline{\mathbf{EDUP}}_{\mathbf{it}}) + \mathbf{e}_{\mathbf{it}} - \overline{\mathbf{e}}_{\mathbf{it}},\ \mathbf{t = 1, 2,\ldots, T} \qquad \textit{(VIII)}$$

Thus the fixed effect transformation is captured as a general time-demeaned equation for each country i

$$\mathbf{BIO^*_{it}} = \beta_1\mathbf{GDPC^*_{it}} + \beta_2\mathbf{GDPC^{2*}_{it}} + \beta_3\mathbf{UPOP^*_{it}} + \beta_4\mathbf{ALANDA^*_{it}} + \beta_5\mathbf{EDUP^*_{it}} + \mathbf{e^*_{it}},\ \mathbf{t = 1, 2,\ldots, T} \qquad \textit{(IX)}$$

The $BIO_{it} - \overline{BIO}_{it}$ is the time-demeaned data of biomass consumption which is similar for all explanatory variables and the idiosyncratic error (e_{it}). The model IX is estimated to obtain the fixed effects estimators. The quadratic function embedded in the time-demeaned equation is to obtain EKC turning point. The turning point income for biomass consumption is the maximum of the quadratic function. In order to capture this diminishing marginal effect of economic growth (Y) on biomass consumption (X), the function takes the form

$$\mathbf{Y} = \beta_0 + \beta_1\mathbf{X} + \beta_2\mathbf{X}^2 \qquad \textit{(X)}$$

An EKC hypothesis will be true when $\beta_1 > 0$ and $\beta_2 < 0$ such that the relationship between X and Y has a parabolic shape or inverted-U as shown in figure 1. The maximum of the function is obtained at a point expressed by the calculus form

$$\dot{x} = \beta_1 / -2\beta_2 \qquad \textit{(XI)}$$

This $\dot{x}$ represents the turning-point income at which maximum biomass consumption is observed in i (Wooldridge, 2006).

Similarly, fixed effects model without the quadratic function was estimated for infant mortality and life expectancy in which income, biomass consumption, urban population and other variables were included as explanatory factors in the model. We investigated a relationship discussed in section 4.3 and illustrated in equation XII.

$$\mathbf{H_i = f\ (Y_i, BIOi, Z_i)} \qquad \textit{(XII)}$$

The equation shows that health (Hi) is dependent on the level of biomass consumption (BIOi), the level of economic growth (Yi) and other social factors (Zi) (see section 4.3). Our analysis could also be subjected to potential biases, which are common in EKC analysis such as measurement errors, data sources and collection problems e.g. cross-country data are subjected to aggregation bias as noted by Plassmann and Khanna (2006).

5.2 CROSS-SECTIONAL DATA ESTIMATION MODEL

Owing to data constraints it was not possible to include some explanatory variables which are important in the fixed effect estimation models for biomass consumption, infant mortality and life expectancy and these are ALANDA, ASANF, ASWATF, DOCT, and IMMU1. Therefore, we consider OLS estimation for cross-section data in order to allow comparison with results obtained from the fixed effects estimation as discussed in chapter 4. Cole et. al., (1997) conducted panel analysis for total energy use and some air pollutants while *'methane and CFCs and halon were subjected to cross-section OLS analysis'*. Although in their work, linear and log-linear relationships were used in the least square estimation model we employ a linear form for biomass consumption (EPi) and health (Hi) as written in equations XIII and XIV respectively.

$$\mathbf{EP_i = \Pi_i + \beta_1 Y_i + \beta_2 Y^2{}_i + \beta_5 Z_i + e_i} \qquad \textit{(XIII)}$$

$$\mathbf{H_i = \Pi_i + \beta_1 Y_i + \beta_2 EP_i + \beta_5 Z_i + e_i} \qquad \textit{(XIV)}$$

6. Results

6.1 Biomass Consumption EKC Analysis

Using panel dataset A, we estimated equation IX for the biomass consumption and results obtained are presented in Table 9. Equation XIII was also estimated using cross-sectional datasets and results obtained are presented in Table 9 as well. Heteroskedasticity was corrected for by obtaining robust standard error while we corrected for autocorrelation by using *xtserial* and *xtregar* commands in STATA 9. In accordance with Stern et. al. (1996)'s comment that cross-sectional data OLS estimation may be subject to bias we report the heteroskedasticity test results (Appendix III).

The panel data EKC estimates reveal that per capita income, urbanization level, and ALANDA significantly influence biomass consumption, whereas the impact of literacy is insignificant. We obtained an inverted-U relationship (a true EKC) from the fixed effects estimation in which biomass consumption initially increases with per capita income and then peak at $119 (1996 US Dollar). This turning point occurs at very low income level. This result is as expected since this level of income is appropriate for a household which shifts from dependence on animal dung to at least a transition fuel (e.g., char coal, kerosene, etc) in the second step of the energy ladder (figure 2). Also as explained in chapter 4, the IEA energy statistics from which the biomass use data was obtained already shows that highest dependence on biomass still occurs in the poorest nations where per capita income is very low. Again, this estimate is similar to the household level study in Guatemala by Foster et. al., (2000) in which the turning point obtained for gross energy consumption per household occurs at US $205. The EKC literature also indicates that pollutants of short term impact usually have a low turning–point income (Arrow et. al., 1995). The EKC turning point of $5000 obtained for commercial energy use by Gangadharan and Valenzuela (2001) is far from our estimates because commercial energy use is predominant in the developed world and not common among the poor households in developing countries where significant consumption of biomass still takes place (IEA, 2004).

As we aim to compare OLS and panel data (fixed effects) estimates, only results from 1990 cross-sectional dataset show a true EKC relationship that is comparable to fixed effects estimate. Here, the turning point estimate is higher than that obtained from panel data analysis but very similar to the estimate of Foster et. al. (2000). Biomass consumption peaks at per capita income level of $266 (1996 US Dollar). This is similar to the results of Cole et. al., (1997) in which OLS estimate for CFC and halons is higher than any of the fixed effect estimates for CO and SO_2.

Furthermore, statistically significant negative coefficient on the level of urban population which implies that as more people live in the urban areas a reduction in dependence on biomass use results and the higher is the potential of shifting to cleaner fuels. Contrarily, the negative coefficient on ALANDA is counter to our expectation. It shows that the higher the level of agricultural production the less is biomass consumption. This could have some relevance in the WTO GATT debates on subsidies on agriculture in which the supporters of 'output model' of agriculture-environment relationship argue that environmental quality co-evolved with agriculture and that they are both complementary goods (Hodge, 2000) claiming that agriculture is multifunctional. The implication here is that some level of agricultural production could be necessary for a reduction in dependence on biomass use and this could be true as agriculture could raise the per capita income level. However, this point is not consistent as a positively significant estimate was obtained on the same variable in OLS estimation for 1990 cross-sectional data which is in line with our expectation and supports the 'input model of agricultural impact on environment' (Hodge, 2000) in which both agriculture and environment are seen as competitive goods. One inference from these divergent results is that estimates from EKC studies depend on the econometrics technique employed in the analysis (Stern et. al., 1996).

In order to again verify the claim of Stern et. al. (1996) that EKC study outcome also depend on the data employed. Results from 2000 and 2004 cross-sectional datasets OLS estimations presented in table 9 show an opposite EKC relationship (U-shape) which is counterintuitive. The positively significant coefficients on the GDP square term imply that biomass consumption increases at higher income levels.

In all the estimations (fixed effects and OLS) we observed a negatively significant coefficient for the level of urbanization (UPOP) which shows that urbanization is a good predictor of biomass use as explained above. On the other hand, level of education is not a significant predictor of biomass consumption in all estimations which run counter to expectation except for 2000 cross-section in which the positive sign on the coefficient indicates that as education level increases in a country the level of awareness about the bad health impact of indoor air pollution increases and thus people tend to reduce biomass use and shift to cleaner fuel. However, coefficients on ALANDA for 2000 and 2004 cross-sections support the 'output model of environmental impact' as earlier discussed which is opposite to the result from 1990 cross-sectional data. In general, while a true EKC is obtained from 1990 cross-sectional data no true EKC was found from 2000 cross-sectional data when both were subjected to same OLS estimation technique. This implies that the data employed for EKC analysis is an important factor determining the outcomes and this is consistent with the claim of Stern et. al. (1996).

6.2 Impact on Population Health

Results of the fixed effect (panel data B) and cross-sectional data OLS estimations of a similar equation to Eq. (IX) with appropriate health variables and Eq. (XIV) respectively are presented in tables 10 and 11. The tables compare the results from both estimation techniques as well as results from different year cross-sectional data. In our estimations, infant mortality (INFM) and life expectancy (LIFE) are the endogenous variables. Tables 10 and 11 report the impact of biomass consumption (BIO) on these variables respectively. We considered that some additional explanatory variables of which panel data could not be obtained which are missing out of the fixed effect model *(HIV, ASANF, AWATF: see table 4)* could biased our estimates and therefore we included those variables in the 2004 cross-sectional OLS model in order to make comparison with other cross-section results. It however became intuitive to think that there could be significantly high correlation between these health variables and urban population but correlation coefficients obtained which are shown in table 8 prove opposite and we employ them in our models.

In the fixed effect estimations results (both INFM and LIFE), only the coefficients on biomass consumption and GDP have signs as expected while UPOP which is already considered to exhibit an ambiguous relationship has a positive association with infant mortality and a negative association with life expectancy. The fixed effect results imply that biomass consumption is a significant determinant of population health. It signifies that as biomass consumption increases, infant mortality rate rises while life expectancy falls. In both cases, GDP is significant and the signs indicate that as income level rises infant mortality decreases and life expectancy increases which is intuitive.

In the case of UPOP, the positive sign on the coefficient when INFM is the dependent variable implies that while environmental improvement (biomass use reduction) is achieved with increasing level of urbanisation, the feedback effect of economic growth through urban air pollution on health is significant and thus the environmental gains at early stages of economic growth cancels out the health gains which led to increase in infant mortality rate.

Also, this is confirmed with the negative relationship obtained for life expectancy which means that as urbanisation increases life expectancy falls. As discussed in section 4 that other factors, such as tobacco consumption could be responsible for adult life expectancy increasing urban air pollution could reduce the life expectancy. The results of two-stage least square (2SLS) estimation by Gangadharan and Valenzuela (2001) on the impact of CO_2, SO_2, and NOx, which are common urban air pollutants show negative significant relationships with life expectancy while positive relationship of CO_2 with the level of urban population in the same paper indicates that urban air pollution increases with urbanisation. We observe that the number of physicians per proportion of the population (DOCT) has a negative impact on infant mortality rate although not significant (fixed effect). At the same time, it appears that the level of education has no significant impact on life expectancy similarly to the results of fixed effect EKC analysis discussed above. The signs on the coefficients for level of immunization (IMMU1) as shown in table 10 column 2 indicates that it does not decrease infant mortality rate but rather opposite.

However, the coefficients from our OLS estimates for impact of DOCT on life expectancy have expected signs and the 2000 cross-section result shows that DOCT variable has a significant impact on life expectancy. This OLS estimate is similar to 2SLS estimate from Gangadharan and Valenzuela (2001). Also, results from all the OLS estimations indicate that the level of immunization significantly reduces infant mortality and increases life expectancy.

Again, in all OLS estimations, level of education exerts a significant impact on infant mortality and life expectancy with coefficient signs as predicted. In table 10, the results show that infant mortality decreases as level of education increases while in table 11 the results indicate that life expectancy rises as the level of education increases. Similar situation occurs for IMMU1 and DOCT in both cases which are consistent with our expectation as discussed in chapter 4.

However, we obtained interesting results for the impact of level of urbanisation on health. First, the sign on all coefficients obtained from OLS estimation of cross-sectional data are the same but opposite in both cases when life expectancy and infant mortality are dependent variables. In table 10 all coefficients (1990, 2000 and 2004) for UPOP show that increases in the level of urbanisation results in reduction in infant mortality which is significant in 1990 and 2000 while in table 11 the results implies that as the level of urbanisation increases life expectancy also increases and this is significant in 1990 and 2000 as well. In both cases, the sign on the UPOP coefficients for fixed effects is opposite to those of OLS cross-section estimates. This also implies that claim of Stern et. al. 1996 (that EKC study outcome depend on estimation technique used) may not only hold for EKC but also in the health analysis.

When we included other variables which we consider important estimators of population health in 2004 cross-section OLS estimation it was observed that biomass consumption does not show a significant impact on health and the sign on the coefficient is opposite to our expectation when infant mortality and life expectancy are used as dependent variables. Generally, the result comparison shows that our fixed effect estimate with less explanatory variables better explain the impact of biomass consumption on health than OLS cross-section estimate with more explanatory variables (see tables 10 and 11).

Table 9: The effect of per capita income (GDP), population, agricultural production and education on biomass consumption per capita

Explanatory Variable	Panel Data Estimation A (Fixed effects)	1990 Cross Sectional Data Estimation (OLS)	2000 Cross Sectional Data Estimation (OLS)	2004 Cross Sectional Data Estimation (OLS)
	COEFF (R.SE)	**COEFF (SE)**	**COEFF (SE)**	**COEFF (SE)**
Constant	0.25468***	0.6419**	0.27291**	1.63101
	(0.2784)	(0.2443)	(0.12710)	(1.23238)
GDPC	0.00068***	0.0213*	-0.00403	-0.01666*
	(0.00023)	(0.02180)	(0.00156)	(0.00346)
GDPC2	-2.86E-06**	-0.00004**	0.00002*	0.00005*
	(1.37E-06)	(0.00001)	(0.00001)	(0.00003)
UPOP	-0.00122**	-0.0098***	-0.00350***	-0.00152*
	(0.00060)	(0.0121)	(0.00070)	(0.00088)
ALANDA	-0.10649***	0.4168***	-0.18629*	-0.00547**
	(0.04240)	(0.8595)	(0.10375)	(0.00258)
EDUP	-0.00003	-0.0023	0.00104	-0.01328
	(0.00013)	(0.0031)	(0.00137)	(0.01152)
F-test	9.46	9.65	10.66	3.04
R^2	0.0637[b]	0.3567	0.2363	0.1280
Autocorrelation F-statistic[a]	-	0.2705	0.7950	0.0476
Heteroskedasticity F-statistic[a]	-	7.6376	0.8572	4.1053
Hausman's x^2	5.96	-	-	-
Turning Point (1996 US $)	**119** **True EKC**	**266** **True EKC**	**101** **Opposite EKC**	**167** **Opposite EKC**

a – see appendix I for output, b - R^2 (within), COEFF – Coefficient, R.SE: Robust Standard Error, SE: Standard Error
*** 1% significance level; ** 5% significance level; * 10% significance level

Table 10: The effect of per capita income (GDP), biomass consumption and other explanatory variables on health of the population (Dependent Variable: Infant Mortality)

Explanatory Variable	**Panel Data Estimation B (Fixed effects)**	**1990 Cross Sectional Data Estimation (OLS)**	**2000 Cross Sectional Data Estimation (OLS)**	**2004 Cross Sectional Data Estimation (OLS)**
	COEFF (R.SE)	COEFF (SE)	COEFF (SE)	COEFF (SE)
Constant	6.45572 (12.93299)	162.27370*** (15.67045)	163.14160*** (19.71510)	208.3832*** (19.2496)
BIO	0.000224* (0.00017)	0.00002 (0.00003)	9.10E-07 (0.00005)	-7.03E-06 (0.00007)
GDP	-0.00021*** (0.00007)	-0.00218*** (0.00035)	-0.00113*** (0.00022)	-0.00116*** (0.00021)
EDUP	0.10171** (0.03631)	-0.40667*** (0.15255)	-0.39558** (0.18534)	-0.45506** (0.16075)
UPOP	0.49838*** (0.13380)	-0.28355** (0.14133)	-0.30754*** (0.10261)	-0.01980 (0.09665)
IMMU1	0.78050*** (0.17750)	-0.65712*** (0.14459)	-0.62699*** (0.13696)	-0.89041*** (0.16894)
DOCT	-0.00233 (0.03140)	-4.77887*** (1.78582)	-4.19996*** (1.27724)	-0.43347 (1.62834)
HIV	-	-	-	0.38124* (0.21787)
ASANF	-	-	-	-0.10706 (0.12747)
AWATF	-	-	-	-0.33794** (0.14114)
F-test	10.91	57.94	43.00	26.78
R-squared	0.1625	0.7321	0.7062	0.6789
Heteroskedasticity F-statistic[a]	-	1.15358	0.8333	0.0647
Autocorrelation F-statistic	-	0.10300	0.4468	1.0157
Hausman's x^2	14.82			

a: see appendix I for output, b: R^2 (within), COEFF – Coefficient, R.SE: Robust Standard Error, SE: Standard Error;
*** 1% significance level, ** 5% significance level, * 10% significance level

Table 11: The effect of per capita income (GDP), biomass consumption and other explanatory variables on health of the population (Dependent Variable: Life Expectancy)

Explanatory Variable	Panel Data Estimation B (Fixed effects)	1990 Cross Sectional Data Estimation (OLS)	2000 Cross Sectional Data Estimation (OLS)	2004 Cross Sectional Data Estimation (OLS)
	COEFF (SE)	COEFF (SE)	COEFF (SE)	COEFF (SE)
Constant	200.1858***	34.64298***	24.21771***	27.728***
	(18.1257)	(3.31922)	(6.08382)	(5.29759)
BIO	-0.00032***	-1.84E-06	0.00002	8.77E-06
	(0.00009)	(0.00001)	(0.00003)	(0.00006)
GDP	0.00019**	0.00060***	0.00036***	0.00036***
	(0.00008)	(0.00011)	(0.00007)	(0.00006)
EDUP	-0.00416	0.11398***	0.10201*	0.1049**
	(0.01849)	(0.03785)	(0.06116)	(0.04550)
UPOP	-0.86126***	0.07377**	0.11965***	0.00993
	(0.11732)	(0.03639)	(0.03644)	(0.02842)
IMMU1	-1.50851***	0.15123***	0.2370***	0.23021***
	(0.31253)	(0.04133)	(0.04870)	(0.04651)
DOCT	-0.14852***	0.39432	1.56256***	0.04790
	(0.02623)	(0.51815)	(0.45045)	(0.45114)
HIV	-	-	-	-0.49067***
				(0.06003)
ASANF	-	-	-	0.05170
				(0.03505)
AWATF	-	-	-	0.05896
				(0.03909)
F-test	91.19	47.73	33.51	42.54
R-squared	0.6759	0.7197	0.6850	0.7752
Heteroskedasticity F-statistic[a]	-	0.08685	0.8333	3.044913
Autocorrelation F-statistic	-	0.97746	0.8572	3.0449
Hausman's x^2	32.20	-		-

a – see appendix I for output, b - R^2 (within), COEFF – Coefficient, R.SE: Robust Standard Error, SE: Standard Error
*** 1% significance level, ** 5% significance level, * 10% significance level

7. Conclusions, Policy Implications and Future Research

This study extends the debate on the relationship between environment and economic growth by investigating the links between biomass consumption, health and income. Similarly to Panayotou (1997), we believe that environmental pollution, studied as biomass consumption in this paper, increases with income and decreases at higher levels of income. Many macro level EKC studies have shown various evidences for local air pollutants; none has investigated biomass, where only a handful of micro, household level studies have examined the EKC hypothesis for biomass consumption.

We therefore begin by first looking at the existence of EKC relationship for biomass consumption and find a true EKC for traditional biomass fuels, with a turning point at a very low income level, consistent with our hypothesis. Although this result implies that economic growth can be depended upon as a policy solution the existence of feedback effect of indoor air pollution on health at early stages of economic growth negates the health gains brought about by increased income level as biomass consumption was found to significantly affect population health. Therefore, poor countries where use of traditional fuels is still predominant (IEA, 2006) can not simply depend on economic growth without attending to environmental problems, such as use of biomass.

We recommend that instead of following the path taken by the developed countries especially United Kingdom and United States in 1950s when a shift to Coal led to serious health impacts (Victor and Victor, 2002) a climb to cleaner energies, such as solar for household use would be appropriate in this era considering the global concern about the implications of methane and CO_2 on climate change. Although solar technologies are expensive, support from international organizations may be important in achieving this energy limb (a shift from biomass use to solar) through research and funding.

Another important reason why this energy limb is necessary for developing countries is that even if the low level of economic growth found in this study is achieved, the impact of biomass use on health before this level is attained can make the population return to biomass use, creating a "low income-biomass-poor health-biomass-low income" vicious circle: A household that has depended on burning of animal dung and firewood for cooking is at high risk of developing bronchitis in the future. Since it is well recognized that poor health leads to reduction in labour productivity a household that had climbed to the top of energy ladder can climb down to biomass fuel if the resultant effect of indoor air pollution which it had been exposed to manifests in the future. In fact, 'poor health is more than just a consequence of low income; it is also one of its fundamental causes' (Bloom and Canning, 2001). Therefore, in order to properly capture the health gains brought about by economic growth policies must be driven towards addressing the use of biomass fuel even before the EKC turning point is reached (Gangadharan and Valenzuela, 2001).

The possible feedback effect of poor health and environmental pollution on income could not be tested because we recognized that a lot of factors apart from these two determine economic growth in a country and data for those factors could not be obtained due to time constraint, a further research is therefore necessary. This is important because it will help open more windows in understanding the black box nature of EKC for developing countries where there is increasing rate of spread of infectious diseases such as HIV/AIDS which could negate positive impact of economic growth by reducing productivity of the labour force.

Again, our results show that panel data fixed effect estimation is better than cross-sectional data OLS estimation for EKC studies and we recommend further study employing a dynamic panel model, since last period's biomass consumption is expected to have impacts on this years' biomass consumption.

References

Aldy, Joseph E. (2005), An Environmental Kuznets Curve Analysis of U.S. State-Level Carbon Dioxide Emissions. *Journal of Environment and Development,* 14(1): 48 – 72.

Anderson, H. R. (1978), Respiratory abnormalities in Papua New Guinea children: the effects of locality and domestic wood smoke pollution. Int J Epidemiol 7:63 – 72.

Atle, John M., and Heidebrink, Greg (1995), Environment and Development: Theoryand International Evidence, *Economic Development and Cultural Change* 43(3): 603 – 25.

Arrow, Kenneth, Bert Bolin, Robert Costanza, Partha Dasgupta, Carl Folke, C. S. Holling, Bengt-Owe Jansson, Simon Levin, Karl-Gôran Mäler, Charles Perrings, David Pimentel. 1995. Economic Growth, Carrying Capacity, and the Environment. *Science* 268: 520–21.

Barbier, E. B. and J. C. Burgess, 2001: The Economics of Tropical Deforestation, Journal of Economic Surveys, vol. 15, no. 3, pp. 413 – 433.

Barbier, E. B. 1997: Environmental Kuznets Curve Special Issue. *Environment and Development Economics* 2: 369 – 381.

Beckerman, W.B., 172. Economic growth and the environment. Whose Growth? Whose environment? *World Development*. 20:481 – 496.

Bhattarai, Madhusudan (2000), The Environmental Kuznets Curve for Deforestation in Latin America, Africa, and Asia: Macroeconomic and Institutional Perspectives. Dissertation, Clemson University, Clemson, SC, December.

Bloom, David E. and Canning, David, (2000), The Health and Wealth of Nations. *Science*, 18 Feb. 2000, 287, pp. 1207 -9

Bruce N, Perez-Padilla, R., Albalak, R (2000), Indoor air pollution in developing countries: a major environmental and public health challenge. Bull WHO 78: 1078 – 1092.

Bruce, N.; Perez-Padilla, R. and Albalak, R. (2000). Indoor Air Pollution in Developing Countries: a Major Environmental and Public Health Challenge. *Bulletin of the World Health Organisation*. 78 (9), pp. 1078 – 92.

Clay, Rebecca (2002), Renewable Energy: Empowering the Developing World. *Environmental Health Perspectives,* Vol. 110, No. 1. pp. A30 – A33.

Cole, M.A., Rayner, A. and Bates, J.M. (1997), The environmental Kuznets curve: an empirical analysis, Special Issue on Environmental Kuznets Curves. *Environmental and Development Economics* 2 (4): 401 416.

Cropper, Maureen, and Griffiths, Charles (1994), The Interaction of Population Growth and Environmental Quality. *American Economic Review.* Papers and Proceedings 84(2): 250–54.

Davis, Mark. 1998. "Rural household energy consumption: the effects of access to electricity–evidence from South Africa. *Energy Policy,* 26(3): 207-217.

De Almeida and de Oliveira. 'Brazilian Lifestyle and Energy Consumption' *Energy Demand, Lifestyle and Technology.* World Energy Council. London: WEC. 1995.

de Bruyn, Sander M. (2000), Economic Growth and the Environment. *Kluwer Academic Publishers, London,* Vol. 18. Chapter 5.

Duraiappah, Anantha K. (1998), Poverty and Environmental Degradation: A Review and Analysis of the Nexus. *World Development* Vol. 26, No. 12, pp 2169 – 2179.

Duncan G. (1996), 'Income dynamics and health.' in Michaela Benzeval, Jayne Taylor and Ken Judge, 2000. Evidence on the Relationship between Low Income and poor Health: Is Government Doing Enough?. *Fiscal Studies* Vol. 21 (3), pp. 375 – 399.

Dzioubinski, Oleg and Chipman, Ralph (1999), Trends in Consumption and Production: Household Energy Consumption. UN Economic and Social Affairs ST/ESA/1999/DP. 6 DESA *Discussion Paper* No. 6. http://www.un.org/esa/papers.htm.

Elias, Rebecca J. and Victor, David G. (2005). Energy Transitions in Developing Countries: a Review of Concepts and Literature. *Working Paper* ₦ 40. Program on Energy and Sustainable Development, Centre for Environmental Science and Policy, Stanford University. http://pesd.stanford.edu.

Ellis, Frank (1998), Livelihood Strategies and Rural Livelihood Diversification. *The Journal of Development Studies.* 35 (1): 1-38.

Ehrhardt-Martinez, Karen, Crenshaw, Edward M., and Jenkins, J. Craig (2002), Deforestation and the Environmental Kuznets Curve: A Cross- National Investigation of Intervening Mechanisms. *Social Science Quarterly* 83(1): 226–43.

Ezzati M, Saleh, H. and Kammen D.M (2000). The contributions of emissions and spatial microenvironments to exposure to indoor air pollution from biomass combustion in Kenya. *Environmental Health Perspectives*, 108: 833 – 839.

Ezzati, M. and Kammen, D. M. (2002). The Health Impacts of Exposure to Indoor Air Pollution from Solid Fuels in Developing Countries: Knowledge, Gaps, and Data Needs. *Environmental Perspectives,* Vol. 110, No. 11 , pp. 1057 – 1068.

Foster, Vivien, Jean-Philippe, Tre, and Quentin, Wodon (2000), Energy consumption and income: an inverted U- at the household level? The World Bank.

Gangadharan, Lata and Valenzuela, Ma. Rebecca (2001), Interrelationships between income, health and the environment: extending the Environmental Kuznets Curve hypothesis. *Ecological Economics* 36: 513 – 531.

Grossman, Gene M. and Alan B. (1991), Environmental Impact of a North American Free Trade Agreement. NBER Working Paper 3914.

Heltberg, Rasmus (2003), Household Fuel and Energy Use in Developing Countries – A Multicountry Study. *Draft for Discussion.* Oil and Gas Policy Division. The World Bank.

Hirdes, J.P., Brown, K.S., Forbes, W.F., Vigoda, D.S. and Crawford, L. (1986), 'The association between self-reported income and perceived health based on the Ontario longitudinal study of aging', in Michaela Benzeval, Jayne Taylor And Ken Judge, 2000. Evidence on the Relationship between Low Income and poor Health: Is Government Doing Enough?. *Fiscal Studies.* Vol. 21 (3), pp. 375 – 399.

Hodge, Ian (2000), Agri-environmental relationships and the choice of policy mechanism, *The World Economy* 23 (2) 257 – 273.

International Energy Agency (IEA), (2000), CO2 emission from fuel combustion intensity, 1971 – 1998. OECD, Paris.

IEA (2004), International Energy Agency, World Energy Outlook 2004. Energy and Development (Chapter 10).

IEA (2006), International Energy Agency, World Energy Outlook 2006. Energy for Cooking in Developing Countries (Chapter 15). www.worldenergyoutlook.org/weo/pubs/weo2002/energypoverty.pdf

Intergovernmental Panel on Climate Change. IPCC Special Report on Emissions Scenarios. http://www.grida.no/climate/ipcc/emission/index.htm

Jiang, Leiwen and O'Neill, Brian (2003), The Energy Transition in Rural China, International Institute for System Dynamic Analysis, Interim Report IR-03-070.

Jiang, Leiwen and O'Neill, Brian (2004), The Energy Transition in Rural China, *Int. J. Global Energy Issues,* Vol. 21, Nos 1/2.

Judson, Ruth A., Schmalensee, Richard and Stoker, Thomas M. (1999), Economic Development and the Structure of the Demand for Commercial Energy, *The Energy Journal,* Vol. 20, No. 2. 29 – 57.

Leach, Gerald (1992), "The energy transition" *Energy Policy*, February: 116-123.

Lenzen, Manfred, Wier, Mette, Cohen, Claude, Hayami, Hitoshi, Pachauri, Shonali, and Schaeffer, Roberto (2003), A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. *Energy.* 31. 181 – 207.

Masera, R., Barbara, D., Saatkamp, and M. Kammen, (2000), From linear fuel switching to multiple cooking strategies: A critique and alternative to the energy ladder model, *World Development*, 28(12): 2083-2103.

McCracken JP and Smith KR (1998), Emissions and efficiency of improved wood burning cookstoves in highland Guatemala. *Environ Int* 24: 739 -747.

Millimet, Daniel L., John, A. List and Thanasis, Stengos (2003), The Environmental Kuznets Curve: Real Progress or Misspecified Models? *The Review of Economics and Statistics,* 85(4): 1038 – 1047.

Neumayer, Eric (2004), National carbon dioxide emissions: geography matters. *Royal Geographical Society.* 36.1, 33-40.

Panayotou, T. (1993), Empirical tests and policy analysis of environmental degradation at different stages of economic development. Technology, Environment and Employment, Geneva: International Labour Office.

Panayotou, T. (1995), Environmental Degradation at Different Stages of Economic Development. In *Beyond Rio: The Environmental Crisis and Sustainable Livelihoods in the Third World,* ed. I. Ahmed and J. A. Doeleman. London: Macmillan, 13-36.

Panayotou, T. (1997), Demystifying the environmental Kuznets curve: turning a black-decomposing EKC black box into a policy tool. *Environment and Development Economics* 2: 465 – 484.

Panayotou, T. (2003), Economic Growth and Environment, *Economic Survey of Europe,* No. 2 (Chapter 2). http://www.unece.org/ead/pub/032/032_c2.pdf.

Plassmann, Florenz and Khanna, Neha (2003). Household Income and Pollution: Implications for the Debate About the Environmental Kuznets Curve Hypothesis. *The Journal of Environment and Development,* Vol. 15, No. 1, 22 – 41.

Plassmann, Florenz and Khanna, Neha (2006). Household Income and Pollution: Implications for the Debate About the Environmental Kuznets Curve Hypothesis. *The Journal of Environment and Development,* Vol. 15, No. 1, 22 – 41.

Porrit, Jonathon, Zhores Medvedev, Hermann Bondi, Walter Marshall, Denis Rooke, Peter Hardi, John Rae and Peter Chester, 1993. Energy and the Environment. *Oxford University Press.*

Rehfuess, Eva. Fuel for Life: Household Energy and Health. WHO Library Cataloguing-in-Publication Data. ISBN 92 4 156316 1.

Rehfuess, Eva, Mehta, Sumi and Pruss-Ustun, Annette (2006), Assessing Household Solid Fuel Use: Multiple Implications for the Millennium Development Goals. *Environmental Health Perspectives,* Vol. 114, No. 3. pp. 373-378.

Reddy, Amulya K.N. and Reddy, B. Sudhakara (1994). Substitution of Energy Carriers for Cooking in Banglore. *Energy,. 19 (5), pp. 561 – 71.*

Saatkamp, Barbara D., Omar R. Masera and Daniel M. Kammen. "Energy and health transitions in development: fuel use, stove technology and morbidity in Jaracuaro, Mexico.

Sander M. de Bruyn (2000), Economic Growth and the Environment. *Kluwer Academic Publishers, London,*Vol. 18. Chapter 5.

Schirnding, Y., Bruce, N., Smith, Kirk, Ballard-Tremmeer, G., Ezzati, M. and Lvovsky, K. (2002), Addressing the Impact of Household Energy and Indoor Air Pollution on the Health of the Poor: Implication for Policy Action and Intervention Measures. *Paper Prepared for the Commission on Macroeconomics and Health,* World Health Organisation

Selden, T.M. and Song, D. (1994), Environmental quality and development: is there a Kuznets curve for air emissions?. *Journal of Environmental Economics and Management* 27: 471-479.

Shafik, N. and Bandyopadhyay, S. (1992), Economic Growth and Environmental Quality: Time –series and cross-country evidence. World Bank, Working Papers WPS 904, Washington DC.

Simon, J.L. (1977), The Economics of Population Growth. Princeton University Press, Princeton, New Jersey.

Smith, K. R. and Mehta, S. (2000), Background paper for USAID/WHO Global Consultation on the health impact of Indoor Air Pollution and Household Energy in Developing Countries. Washington DC.

Smith K. R., Mehta S, and Feuz, M (2002), *The global burden of disease from indoor air pollution: results from comparative risk assessment* in Indoor Air 2002: Proceedings of the 9th International Conference on Indoor Air Quality and Climate, Monterey, CA, vol 4. Santa Cruz, CA: Indoor Air 2002, 2002; 10 -19.

Smith, Ken R. and Cathleen D. Zick (1994), Linked Lives, Dependent Demise? Survival Analysis of Husbands and Wives in Michaela Benzeval, Jayne Taylor And Ken Judge, 2000. Evidence on the Relationship between Low Income and poor Health: Is Government Doing Enough?. *Fiscal Studies* Vol. 21 (3), pp. 375 – 399.

Sofoluwe, G. O. (1968), Smoke pollution in dwellings of infants with bronchopneumonia, *Arch Envrion Health*. 16:670 – 672 (1968).

Stern, D., Common, M.S. and Barbier, E. B. (1996), Economic growth and environmental degradation: the environmental Kuznets curve and sustainable development, *World Development* 24 (7): 757 – 773.

Sun, J. W. (2002), The sufficient condition needed to make CO_2 emission intensity lower than energy intensity. *Energy Policy.* 30 (2) 165 – 166.

Sun, J. W. (2003), Three types of decline in energy intensity – an explanation for the decline of energy intensity in some developing countries. *Energy Policy.* 31, 519 – 526.

Torras, Mariano and Boyce, James K. (1998), Income, inequality, and pollution: a reassessment of the environmental Kuznets Curve. *Ecological Economics* 25 (1998) 147 – 160.

United Nations (2006), Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, *World Population Prospects: The 2006 Revision* and *World Urbanization Prospects: The 2005 Revision*, http://esa.un.org/unpp.

Victor, Nadejda M. and Victor, David G. (2002), Macro Patterns in the Use of Traditional Biomass Fuels, *Working Paper.* Stanford, CA: Program on Energy and Sustainable Development. 2002.

Viswanathan, Brinda and Kumar, K. S. (2005), Cooking fuel use pattern in India: 1983 – 2000. *Energy Policy.* 33: 1021 – 1036.

World Health Organisation (WHO) (2000), Addressing the Links between Indoor Air Pollution, Household Energy and Human Health. Global Consultation on the Health Impact of Indoor Air Pollution and Household Energy in Developing Countries. WHO/HDE/HID/02.10.

WHO (2000), Addressing the Impact of Household Energy and Indoor Air Pollution on the Health of the Poor: Implication for Policy Action and Intervention Measure. Paper Prepared for the commission on macroeconomics and health *(Working Group 5: Improving Health Outcomes of the Poor).* WHO/HDE/HID 02.9.

WHO (2002), Reducing Risks, Promoting a Healthy Life. *World Health Report*, Geneva.

World Health Organisation (WHO). Indoor Air Pollution, Health and the Burden of Disease. *Indoor Air Thematic Briefing 2.* Department for the Protection of the Human Environment. http://www.who.int/indoorair

WHO (2005). Indoor Air Pollution and Health. Fact sheet No 292, June 2005. http://www.who.int/mediacenter/factsheets/fs292/en/print.html.

Yandle, Bruce, Bhattarai, Madhusudan, and Vijayaraghavan, Maya (2004), Enviornmental Kuznets Curves: A Review of Findings, Methods, and Policy Implications, *Research Study* 02-1. 1 – 38.

Yeh, Ethan (2004), Indoor air pollution in developing countries: Household use of traditional biomass fuels and the impact on mortality. *Dissertation.* Univeristy of California, Berkeley.

APPENDIX

LIST OF COUNTRIES INCLUDED IN PANEL DATASET A

1	Albania	47	Jordan
2	Algeria	48	Kazakhstan
3	Angola	49	Kenya
4	Argentina	50	Korea, DPR
5	Armenia	51	Kuwait
6	Azerbaijan	52	Kyrgyzstan
7	Bahrain	53	Latvia
8	Bangladesh	54	Lebanon
9	Belarus	55	Libya
10	Benin	56	Lithuania
11	Bolivia	57	Former Yugoslav Republic of Macedonia
12	Bosnia and Herzegovina	58	Malaysia
13	Botswana	59	Malta
14	Brazil	60	Republic of Moldova
15	Brunei Darussalam	61	Morocco
16	Bulgaria	62	Mozambique
17	Cameroon	63	Myanmar
18	Chile	64	Namibia
19	People's Republic of China	65	Nepal
20	Colombia	66	Netherlands Antilles
21	Congo	67	Nicaragua
22	Democratic Republic of Congo	68	Nigeria
23	Costa Rica	69	Oman
24	Cote d'Ivoire	70	Pakistan
25	Croatia	71	Panama
26	Cuba	72	Paraguay
27	Cyprus	73	Peru
28	Dominican Republic	74	Philippines
29	Ecuador	75	Qatar
30	Egypt	76	Romania
31	El Salvador	77	Russia
32	Eritrea	78	Saudi Arabia
33	Estonia	79	Senegal
34	Ethiopia	80	Serbia and Montenegro
35	Gabon	81	Singapore
36	Georgia	82	Slovenia
37	Ghana	83	South Africa
38	Guatemala	84	Sri Lanka
39	Haiti	85	Sudan
40	Honduras	86	Syria
41	India	87	Tajikistan
42	Indonesia	88	United Republic of Tanzania
43	Islamic Republic of Iran	89	Thailand
44	Iraq	90	Togo
45	Israel	91	Trinidad and Tobago
46	Jamaica	92	Tunisia

LIST OF COUNTRIES

93	Turkmenistan	113	Hungary
94	United Arab Emirates	114	Iceland
95	Ukraine	115	Ireland
96	Uruguay	116	Italy
97	Uzbekistan	117	Japan
98	Venezuela	118	Korea
99	Vietnam	119	Luxembourg
100	Yemen	120	Mexico
101	Zambia	121	Netherlands
102	Zimbabwe	122	New Zealand
103	Australia	123	Norway
104	Austria	124	Poland
105	Belgium	125	Portugal
106	Canada	126	Slovak Republic
107	Czech Republic	127	Spain
108	Denmark	128	Sweden
109	Finland	129	Switzerland
110	France	130	Turkey
111	Germany	131	United Kingdom
112	Greece	132	United States

ACKNOWLEDGEMENT

I sincerely appreciate the help of Dr. Ekin Birol. She has been the best supervisor I have ever known and her genuine guidance led to the successful completion of this dissertation. I also thank Dr. Andreas Kontoleon for introducing STATA 9 to me and for his patience when I asked many questions. I would also like to thank Wendy Thurley (The Librarian) for her assistance in easily locating books I used when writing this thesis. I express my gratitude to the Department for International Development (DFID) and Shell for their financial support.