University of Alberta

Towards Measuring the Impact of Ecological Disintegrity on Human Health

by

Lee Edward Sieswerda ©

A thesis submitted to the Faculty of Graduate Studies and Research in partial fulfillment of the requirements for the degree of Master of Science

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Abstract

The relationship between ecological integrity (EI) and human health was approached, for the first time, in this aggregate data, cross-sectional design. Selected surrogate measures of EI (e.g., land disturbance) and socio-economic confounders were modeled in three linear main effects regression models with life expectancy, infant mortality, and percent low birth weight as dependent health outcomes respectively. The results are presented using added-variable plots. GDP per capita, a socio-economic rather than an EI variable, was the single strongest determinant, positively influencing health, and required special handling. Conversion of natural areas to human use was associated with improving health, deforestation was associated with worsening health, and percent species threatened and land protection had no relationship. High GDP countries may be experiencing some negative impacts. Being exploratory, however, the models developed require cautious interpretation and further examination, especially in relation to outlier countries that influence trends. Longer-term data would enhance future modeling.

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List of Symbols, Nomenclature, or Abbreviations

CO_2	Carbon Dioxide
EI	Ecological Integrity
FAO	Food and Agriculture Organization (of the United Nations)
GDP	Gross Domestic Product
IBI	Index of Biotic Integrity
IUCN	International Union for the Conservation of Nature
r (R)	correlation coefficient (multiple correlation coefficient)
R^2	coefficient of determination (i.e., percent of variance in the outcome explained by model)
SSHRC	Social Sciences and Humanities Research Council (of Canada)
UAE	United Arab Emirates
UNDP	United Nations Development Program
UNEP	United Nations Environment Program
UNESCO	United Nations Educational Scientific and Cultural Organization
UNPD	United Nation Population Division
US/USA	United States of America
UK	United Kingdom
WB	World Bank
WCMC	World Conservation Monitoring Centre
WHO	World Health Organization
WR	World Resources
WRI	World Resources Institute

Chapter 1 - Ecological Integrity: Overview of the Literature

1.1 Introduction

Concern over the health effects of diminishing ecological integrity (EI), defined explicitly in section 1.2, has arisen alongside the realization that humans are reshaping all regions of the globe, and that this change has unknown consequences. Of growing concern is that this change is occurring not on the natural scales of geologic time, but on a greatly compressed time scale of human generations (Robinson 1994).

Many scientists and non-scientists have provided evidence supporting the premise that EI is rapidly decreasing on this planet. McMichael's (McMichael 1993) overview is perhaps the most useful for the epidemiologist given its health-based approach. He discusses the perils of population increases, climate change, stratospheric ozone depletion and UV radiation, intensive agricultural and aquacultural impacts, loss of biodiversity and forests, and other environmentally-mediated hazards to human health.

Modeling the complexity of nature is, at best, difficult; modeling it accurately requires pushing the bounds of possibility with current technology. The workings of the ecosphere are poorly understood, mainly owing to the vast complexity of these systems. Technology has allowed us to monitor tidal flows, seismic events, atmospheric conditions, biodiversity, and other events. However, while we have become more adept at gathering data, we have not made the same advancements in theoretical understanding – in assessing cause and effect, especially for large, complex systems. The more we learn about Earth's life support systems, the more we realize how little is actually known. Notwithstanding this uncertainty, the importance of this subject for the future of life on Earth cannot be overstated. Some authors (Smith 1994) (Mason 1992) have suggested that humanity has as little as two to three generations before EI has diminished to the point where adaptive strategies will not be optional, but will, in fact, be necessary for survival. The uncertainty inherent in such predictions and in science in general, needs to be recognized as a limitation to society's expectations of science as providing the basis for policy. Despite this uncertainty, scientific data are being assembled through the SSHRC grant #806-96-0004 that is lending concern to these issues.

Work done by Rees (Rees 1996a) suggests convincingly that we are consuming far more than the Earth can sustain. In fact, his calculations show that we would in fact need three Earths to support our current level of consumption (Wackernagel and Rees 1996). This message is an alarming one since, of course, we have only one Earth. Rees's work is based on two fundamental ideas: ecological capital and ecological footprints (Rees 1996b; Wackernagel and Rees 1996). Earth has been accumulating biomass for about 3.5 billion years. In that time, vast deposits of fossil fuels, forests, abundant oceans, fertile soils, and other resources have accumulated. These accumulated resources are what Rees (Rees 1996b) calls ecological capital, and it is only relatively recently that humans have begun to exploit and deplete the Earth's ecological capital. The amount of land required to support a given population's level of consumption is termed its ecological footprint. It has been shown that any concentrated population centre requires far more land to support its inhabitants than the actual land that the population occupies. In other words, the ecological footprint of a city extends far into the surrounding countryside that supports the activities of the city. In fact, with the global economy, the footprint may extend well beyond the boundaries of the country through the purchase of resources from distant producers.

The exploitation of ecological capital has allowed human society to maintain levels of annual consumption far greater than what the global ecosystem can sustainably produce. With the current emphasis on global trading relationships, it becomes readily apparent why a country such as Japan, which has only a small fraction of the land it would require to support its population, can remain so healthy. Japan, like other islands of high population concentration, imports resources, thereby contributing to a global loss of sustainability but avoiding the local ecological effects of this loss. Japan is by no means the only country whose ecological footprint far exceeds its local capacity. A recent chart depicting the respective ecological footprints of 50 countries accounting for some 80% of the world's population is shown in Appendix 1 (courtesy Rees 1998).

Some researchers (in particular, those associated with the Global Integrity Project) have responded to the current ecological crisis with the concept of EI. In this paradigm (i.e., "living in integrity"), human societies would make every effort to minimize their impact on global life support systems. In so doing, societies will maximize EI and presumably forestall, or at least delay, any projected collapse of the biosphere. A major focus of the ecological literature is concerned with EI, or a subtle variant of it. EI also may be referred to as conservation; ecosystem, ecological, or environmental health;

environmental integrity; regional integrity; and a host of other names. The language of the EI phenomenon is not standardized, although some attempts are being made by the Global Ecological Integrity Project (see below).

One of science's emerging realizations is that the properties of a large system cannot be entirely explained by summing the properties of its subsystems (Kay 1991). In line with this realization, Shy (Shy 1997) and others have called for some epidemiologists to broaden rather than to narrow the focus of their studies. He is calling for more research into measuring the effects of larger, system-level characteristics or "exposures" on entire populations.

For instance, how does diminishing biodiversity (a component of EI) affect human health? It is not a simple matter of the direct effect of an exposure on a specific disease outcome. Rather, there may be many causal steps mediating between the loss of biodiversity and human health; for example, the loss of biological compounds useful for treating disease, or the loss of key species that could lower the productivity of entire ecosystems.

The study design employed here is too weak to assess causation largely because of the absence of one of the major positive criteria for causality, namely biological plausibility. This is usually assessed through laboratory investigations. In complex, under-studied fields such as EI, assessing biological plausibility may be difficult. It requires a knowledge of population dynamics and the interplay of populations and their environments that is not nearly as well developed as our medical knowledge of the human body. Correlational studies, however, such as the one undertaken here, are able to provide empirical evidence of which aspects of EI could be targeted for more intensified biological research.

The intent of this study is to contribute to the science dealing with measuring the association between diminishing EI and human health. We have indicated that this is to be a correlational study, but in addition, it should be noted that the correlations are sought at the group level, not at the individual level. The use of group data is reminiscent of the traditionally termed "ecological" study design. In this context, "ecological" has nothing to do with "ecology", but rather refers to the unit of study, which are not individuals, but aggregations of individuals. Commonly, the intent of these ecological studies is to make assertions about individuals based on group data. Unfortunately, this practice of generalizing from groups of people to individuals suffers from the well-known "ecological fallacy" (Robinson 1950). In this study, the units of study are nations not individuals, therefore generalizing our findings to individuals is not a consideration. We have conducted a correlational study using aggregate data, where the aggregations are nations. We, therefore, call our study design an aggregated data study design. There are at least two reasons for doing so. First, the term avoids confusion between the traditional ecological study design, where the underlying intent is to discover something about individuals. Second, the term avoids confusion with the discipline of ecology.

In addition, because we know little about the underlying biological mechanisms that might mediate between EI and the health of populations, no attempt is made to model the actual complex interplay of causal factors with outcomes. Rather, correlations are sought between various intuitively and/or logically predictive factors at the population level and several health-related outcome variables. Key to understanding these studies is that they, in themselves, cannot allow us to draw conclusions regarding cause and effect at either the population level or at the level of the individual person. However, they can lead us in the direction of further research to establish causality.

The latest edition of the biennial World Resources Institute report, World Resources 1998-99 (World Resources Institute et al 1998), focuses on environmental change and human health. Like the present study, it is concerned with the linking of global change and human health data. Unlike our study, however, it does not focus on the idea of EI as articulated by the Global Ecological Integrity Project. Rather than provide measures of broader landscape characteristics, as EI does, WRI has provided new indicators that attempt to summarize some of the specific characteristics of the environment (such as air quality and access to clean water). The WR report (1998-1999) addresses specific environmental threats and discusses their potential threats to human health. Paradoxically, however, with all of the supposed harm to human health of these threats, indicators of human health have been showing improvements for several decades. In the present study, the use of the EI concept as an environmental health indicator has allowed us to transcend the piecemeal approach to environmental threats and to focus on broader landscape issues.

1.2 Definitions of EI and Health

1.2.1 Definitions of EI

One of the specific tasks of the Global Ecological Integrity Project (SSHRC grant #806-96-0004), and the entire subject of this thesis, is to determine what relationship, if any, exists between EI and human health. It should be noted that while EI relates specifically to the positive ramifications of EI, this study's main thrust is to determine whether declining EI, referred to in this study as ecological <u>dis</u>integrity, has a negative impact on human health.

The definition of EI has been somewhat problematic within the project, owing to the complex nature of the phenomenon. This section will overview some of the extant definitions of EI in the literature, as well as provide an operational definition for the purposes of this thesis. It should be noted that while these definitions are useful and necessary, they represent ideals. We have been constrained in our actual application of these definitions by available data that measure EI, confounders, and health outcomes at the population level.

EI is a term that "designates the property of coherent wholeness, health, and internal well-being that characterizes intact, adaptive, self-regulating, and self-repairing systems" (Robinson 1994) (p. 217). A more specific definition of EI is provided by Loucks: "An ecological system has integrity when it supports and maintains a balanced, integrated, adaptive biological system having the full range of living elements (genes, species, and assemblages), and processes (mutation, demography, biotic interactions, nutrient and energy dynamics, and metapopulation processes) expected in the natural habitat of a region" (Loucks 1998). The definition and measurement of EI is an on-going area of research that has not converged on any widely accepted methods. Despite this lack of consensus, members of the Global Ecological Integrity Project have, according to Miller (Miller 1998), clustered around three main perspectives. Each of these perspectives is important and they are not mutually exclusive.

One of the perspectives has been called Original Integrity (Miller 1998); here EI is defined as that state of nature unmolested by human interference. In agreement with this, Westra (Westra 1994) has suggested that we can define EI as a state of "wildness"; that is, areas have more EI if they are relatively undisturbed by human influence. Karr [e.g., (Karr and Chu 1997)] has defined an Index of Biotic Integrity (IBI) for streams that stresses biodiversity and community structure. It measures deviations in biodiversity and the composition and characteristics of biological communities from the so-called "natural" state before the impact of human activity. A key feature of Karr's IBI is that it stresses *biological integrity*. This is important for the development of indicators of EI because it means that measurements of physical characteristics (such as toxic chemical loads or water clarity) are not necessary. By definition, all biologically important physical characteristics of the environment will be captured by measuring the local biota. In accordance with this perspective, the choices of some of the indicators of EI for this thesis focus on factors likely to reflect the biological condition of the ecosystem.

The second perspective is referred to by Miller (Miller 1998) as Systemic Integrity, whose adherents emphasize that EI should be defined functionally regardless of wildness or similarity to natural state. This perspective focuses on the capacities of ecosystems. From this perspective, a system has EI if it can perform necessary functions, withstand stress, and have the capacity for on-going evolutionary development through the maintenance of a sufficiently diverse gene pool and through minimizing human interference. It does not matter if the system looks nothing like its pre-human state. As yet, measurements of ecosystem function are not widely available, so this part of the definition cannot be adequately implemented. Also, measures of an ecosystem's capacity to withstand stress have not been developed and as such cannot be part of this study.

The third perspective has been termed Socially Defined Integrity (Miller 1998); here EI is defined in terms of the ability for ecological systems to sustain and enhance human values and endeavors. This perspective will not be used in the operational definition of EI in this study for reasons indicated below.

The first two perspectives are essentially biological in nature, and serve well as objective exposure criteria for quantitative epidemiologic research because, unlike the third perspective, they do not necessitate consideration of cultural differences in the valuation of nature. As the name implies, Socially Defined Integrity varies from society to society. In doing a global study, the definition of Socially Defined Integrity would vary for each datum, and hence would not be quantitatively comparable across countries. Thus, the third perspective is sociological in nature and will not be considered here. Accordingly, this thesis adopts as its operational definition of EI the ideas (to the extent possible) of the first two perspectives, Original Integrity and Systemic Integrity, in its selection of indicators of EI.

Original Integrity implies a somewhat arbitrary, pre-human or at least pre-agricultural, starting point. It is arbitrary in the sense that ecological systems are dynamic, and so there was never a so-called "Garden of Eden" that existed and represents the "ideal" state of affairs. Nevertheless, choosing a pre-agricultural starting point is useful, because we know that this environment was both suitable for diverse life forms (including human life) and, owing to the absence of industrial-scale human intervention, it changed over a geological time frame. This relatively slow change allowed ecological systems the evolutionary time to adapt to changing conditions. So, Original Integrity is useful in that it provides us with a starting point. However, there remains the argument, presented by Systemic Integrity, that because systems are dynamic, it does not matter much what existed before, so long as what we have now works. How do we know that an ecological system works when we lack both the knowledge of what constitutes an entire ecosystem and the ability to measure all of its aspects? Combining the two perspectives, we can construct a reasonable operational definition.

We can begin with Robinson's definition (Robinson 1994) (which is similar to the Systemic Integrity perspective) wherein EI "designates the property of coherent wholeness, health, and internal well-being that characterizes intact, adaptive, self-regulating, and self-repairing systems." However, owing to our inability to completely define and measure such a system, we turn to Original Integrity as the baseline against which to measure our current state of EI. Therefore, we define EI operationally in terms of deviations from Original Integrity. Using this definition, we have chosen the following six variables (discussed in more detail in the Materials and Methods section) as indicators of EI: percentage of land highly disturbed by human endeavours, percentage of species threatened, percentage of land protected under IUCN categories I – III and IV-V, forest habitat lost since pre-agricultural times, and annual change in forest cover.

1.2.2 Definition of Health

Human health has been defined by the World Health Organization (WHO) as "a state of complete physical, mental, and social well-being, and not merely the absence of disease or injury" (Evans and Stoddart 1994) (p.28). This definition is far too broad for our purposes here. Nevertheless, we would like to remain true to the idea of general health.

One well-accepted indicator of the general health status of a population is its life expectancy. It has at least two major advantages for this study (Wolfson 1994): 1) life expectancies implicitly account for changes in the age structure and therefore do not require age standardization (this is especially useful when dealing with developing country data where age strata may not be reliably defined); and 2) life expectancies are longitudinal in nature. That is, on average, they reflect all of the known and unknown factors that have influenced a person's longevity over the entire course of their life. Of course, some people can be very sick and still live a long time, and some people can be very healthy and still die young but, on average, sick people do not live as long as healthy people.

A better measure of health would be disability-adjusted life years (DALYs), which more explicitly and accurately than life expectancy, takes into account the poorer quality of life associated with living with morbid conditions or disabilities (Murray and Lopez 1997; Murray and Lopez 1996). Unfortunately, DALYs have only recently been defined and country-level data are not yet available.

In addition to life expectancy, we have chosen two other indicators of general health. Infant mortality and incidence of low birth weight in live newborns were chosen because they are standard measures of health, especially in developing countries, and may provide some contrast with life expectancy. Also, they are particularly sensitive to children's health and mother's health in a way that life expectancy is not. This is perhaps a desirable property because vulnerable populations (i.e., infants) may be more sensitive to ecological disintegrity than adults.

Chapter 2 - Rationale and Study Objectives

To date, the most widespread tool for measuring EI across regions is Karr's Index of Biotic Integrity (IBI) (Karr and Chu 1997; Karr et al 1986). Unfortunately, EI, as gauged by the IBI, has been measured directly only for a small, unrepresentative (for this study) number of sites or geographic regions. In addition, to date, it is only an aquatic index, although Karr suggests that river/stream IBI values can serve as sentinels for terrestrial communities (Karr 1998). Karr is currently working on a terrestrial version of the IBI. Because of its relatively recent introduction and lack of broad coverage, the IBI is not useful for this study, nor is there another useful direct measure of EI. Instead, we must rely on indicators of EI, of which there is no standard set. One of the aims of this study, then, is to choose a number of indicators of EI and determine which of those indicators of EI (described in the Materials and Methods section) are best correlated with human health outcomes.

A second shortcoming in this field of research is the lack of knowledge of exactly what aspects of human health, if any, are affected by diminishing EI. It is not a straightforward problem of determining the effect of a pollutant on the function of a specific organ. Instead, it depends for its solution not on models developed based on individual health outcomes, but rather models based on population health outcomes. In this case, we want to determine the association between wholistic measures of the state of the environment, namely EI, and aggregate health outcomes of entire populations. Because of the lack of knowledge as to what specific outcomes are either most appropriate or important, we will analyze only those population health outcomes (described in the Materials and Methods section) that are well-established indicators of population health.

Confounding is a concern in this study and is especially difficult to control given the lack of a detailed theoretical model. We do know, however, that some socio-economic factors are strongly related to both EI and human health. In particular, it is well-known that, in general, increasing wealth is associated with increasing health (Wilkinson 1992) (Wilkins, Adams, and Brancker 1989; World Resources Institute et al 1998). Wealth also may be associated with decreases in EI. Actually, it is likely that a complex relationship exists between EI and wealth. On the one hand, increasing industrialization and the consequent material wealth that is associated with it is likely to create an industrial infrastructure capable of consuming vast amounts of natural resources as a component of ecological capital. Presumably, this large-scale consumption of natural resources would impact negatively on EI. On the other hand, as countries become quite developed they may begin to insist on new environmental standards the intent of which would be to reinstate and maintain EI. One insight that we may gain from this study is what aspects of wealth are related to both EI and health. Because of this, we will consider measures of wealth (described in the Materials and Methods section) as potential confounders and use various measures of socio-economic well-being (described in the Materials and Methods section) to control for it in our analysis.

Chapter 3 - Materials and Methods

3.1 Study Design

A correlational, aggregate data, study design was employed to determine, on several levels of aggregation as the data permit, if human health can be linked to the large-scale deterioration of EI. In addition to indicators of EI, we also considered the associations among other potentially important covariates, which are not indicators of EI *per se*, but which may be confounded with EI.

Measures of EI served as "exposure" variables in the epidemiological sense. Because the exposures to be measured are complex and not well-understood, several indicators of EI were used as proximate measures of EI in all countries for which such measures were available. There is no standard set of proxies for EI. Therefore, in accordance with the operational definition of EI given above, exposures were chosen according to their plausibility as measures of "intactness" or "wildness" of ecosystems. Because of the use of face validity as a method for selecting covariates, a limitation of this study is the lack of objective criteria for data validity.

3.2 Data Sources

All data, except the Gini Index (discussed in section 3.7), were abstracted from World Resources 1994-95 (World Resources Institute, United Nations Environment Programme, and United Nations Development Programme 1994), World Resources 1996-97 (World Resources Institute et al 1998) and the associated Database Diskettes (list of all available variables in Appendix 2). Gini Index data were obtained from the World Bank Internet site (Deininger and Squire 1997). In total, there are 203 countries in the merged data set; however, there are many missing data points for some of the variables.

3.3 Choice of Indicators and Data Quality

Our basic model began in skeleton form as depicted in Figure 3.3.1. That is, we chose a set of EI variables and examined them as predictors of a set of health outcomes. We also chose a set of socio-economic variables that had the potential to confound the EI-health relationship.

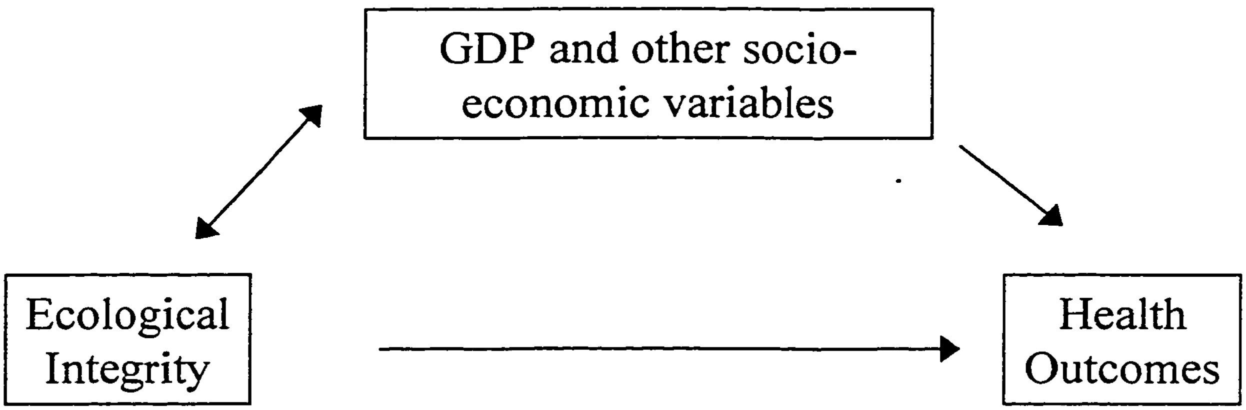

Figure 3.3.1 The simple skeleton model for this study.

As mentioned earlier, there is no standard, agreed-upon set of variables that describe EI. Instead, we took some of the important aspects of the definition of EI and tried to find variables that could be logically connected to parts of the definition of EI. The complete list of EI variables selected from among those listed in Appendix 2 is given in section 3.5 and a more in-depth explanation of each EI variable is given in section 3.6. One of the prominent features of the definition of EI is the emphasis on "wildness". To include this idea in our analysis, we included the percent of land highly disturbed by human activity as one of our EI variables. Another part of the definition of EI is the maintenance of biodiversity, so we chose the percentage of threatened species standardized to a 10,000 square kilometers species-area curve as one variable. Of course, this variable is an admittedly crude way to measure biodiversity. However, it was the best variable that we could find that had global coverage. Sometimes it is recommended that biodiversity could be better preserved by the protection of landscapes rather than individual species. Therefore, we also have included in our analysis the percent of a country's land mass that is totally or partially protected (IUCN categories I-III and IV-V, respectively). In addition, because forests are important ecosystems, and because much data are available on forests, we included two related forest variables: the percent of forest remaining since pre-agricultural times and the average annual change in forest cover.

In choosing potential confounders, we considered that "development" would be a significant confounder. The rationale for this is that richer countries are healthier than poorer countries; we would want to isolate the positive influence of development on health from the negative influences of concurrent environmental degradation. To do this, we examined many indicators of development and included for consideration in our study those that seemed most relevant as indicators of wealth and development. The complete list of potential confounding variables, selected from among those listed in Appendix 2, is given in section 3.5 and a more in-depth explanation of each potential confounding variable is given in section 3.7. In our study, the most obvious example of a variable representing wealth is gross domestic product (GDP) per capita. Related to this, but more related to the industry aspect of development, is industrialization. This is represented in our study by two variables: carbon dioxide (CO_2) emissions per capita and CO_2 per 1,000 hectares. Population is an important issue today. We considered that urbanization and population density may be importantly related to both EI (in that high concentrations of people place large demands on available resources) and to health (especially in poorer countries, population density and poor urban sanitation may increase the transmission of some diseases). Sometimes it is suggested that it is not absolute wealth that is an important predictor of health (as well as being related to EI through resource extraction), but rather income distribution. One measure of income disparity included in this study is the Gini index. Finally, we considered that literacy and education might be important. Education provides information that allows people to make more informed choices regarding both their health and their environment. Ideally, we would want data on both male and female literacy. Unfortunately, some countries do not collect data on that subject. Therefore, we used adult male literacy as an indicator of education at the national level.

To choose health outcomes, we had to come to grips with the lack of a biological model that could adequately predict specific health outcomes. Owing to this gap in knowledge, we opted for some traditional measures of general population health, such as life expectancy, infant mortality, and percentage of low birth weight babies. The complete list of health outcome variables used in this study is given in section 3.5 and a more in-depth explanation of each health outcome variable is given in section 3.8.

Other considerations, besides face validity, in choosing variables included having broad global coverage and a relatively recent collection date (1990-1996).

The data from World Resources was compiled from other sources, mainly United Nations organizations. Owing to the variability in data quality, no blanket statement can be made about the reliability of the variables that we have chosen. However, some notes are provided for individual variables. This will be taken into consideration in the analysis, particularly in the analysis of influential points (i.e., the influence of outliers).

Gini Index data from the Deininger and Squire data set were compiled from multiple sources and the quality is variable. The data for each country have been evaluated by the authors, and only those data rated as "acceptable", and included in the World Bank's "high-quality" data set, were included in our analysis (Deininger and Squire 1997).

It also should be noted that not all data are collected in the same year. This is unfortunate, but unavoidable. Dates of coverage for each variable are noted below.

3.4 List of Study Variables

The following is a list of the variables that were examined in this study. The complete description of each variable is given in the following sections grouped into indicators of EI, potential confounders, and indicators of health.

Indicators of EI (Predictors)

- Percent of land highly disturbed by human activity
- Threatened species (%) (total for mammals, birds, higher plants, reptiles, and amphibians)
- Partially protected areas (International Union for the Conservation of Nature (IUCN) categories IV - V) as a percentage of total area
- Totally protected areas (IUCN categories I - III) as a percentage of total area
- Forest remaining since pre-agricultural times (%)
- Average annual change in forest cover (%) (1981-90)

Potential Confounders (Predictors)

- Carbon dioxide emissions per capita
- Carbon dioxide emissions per 1,000 hectares
- Percentage of population living in urban areas
- Human population per square kilometer
- Gross National Product (GNP) per capita ($US)
- Gross Domestic Product (GDP) per capita (Purchasing Power Parity (PPP)) ($Int)
- Gini Index
- Adult male literacy (%)

Indicators of Health (Outcomes)

- Life expectancy at birth (5-year average)
- Infant mortality rate (5-year average) per 1,000 live births
- Incidence of low birth weight babies (%)

3.5 Indicators of EI

The choice of indicators that best describe EI is influenced mainly by each indicator's potential to reflect our operational definition of EI as described above. That is, each indicator of EI reflects some aspect of human interference with the environment. Reductions in EI are measured as deviations from Original Integrity caused by human activity. Therefore, each indirect measure, or indicator, of EI listed below has been chosen because, at some level, is believed to capture the influence of human activity on ecosystems.

Indicator: Percent of land highly disturbed by human activity

Rationale: Direct measure of habitat disturbance

Year: 1993

Data Source: Conservation International

Data Quality: Measured by satellite map units of a minimum size of 40,000 hectares. This may mean that very small countries (such as small islands) may be poorly classified. Also, WRI states that the underlying data are of variable quality and that areas of low disturbance are likely to be overestimated owing to outdated information.

Other Notes: Definition of low, medium, and high disturbance (quoted from p. 328 of (World Resources Institute, United Nations Environment Programme, and United Nations Development Programme 1994))

Low human disturbance: covered by natural vegetation and/or have a population density of under 10 people per sq. km or under 1 person per sq. km in arid, semiarid, and tundra regions.

Medium human disturbance: under shifting or extensive agriculture, and/or contain secondary, naturally regenerating vegetation; have a livestock density exceeding their carrying capacity; exhibit other evidence of human disturbance (e.g., contain a logging concession); or otherwise do not fit into the other two disturbance categories.

High human disturbance: under permanent agricultural cultivation or urban settlement, and/or contain primary vegetation removed without evidence of re-growth; contain current vegetation differing from potential vegetation; have a record of desertification or other permanent degradation.

Indicator: Threatened species (%) (total for mammals, birds, higher plants, reptiles, amphibians)

Rationale: Measures threats to biodiversity

Year: 1993

Data Source: World Conservation Monitoring Centre (WCMC)

Data Quality: Data for islands and tropical areas are probably under-estimated; taxonomy and extent of knowledge may vary across countries.

Other Notes: Data are adjusted using a species-area curve intended to facilitate comparison across countries (World Resources Institute et al 1998) (page 271); threatened species include those classified as endangered, vulnerable, rare and indeterminate, but not introduced or extinct species (World Resources Institute et al 1998) (p. 270).

Indicator: Partially protected areas (International Union for the Conservation of Nature (IUCN) categories IV - V) as a percentage of total area

Rationale: Measures amount of partially protected land

Year: 1994

Data Source: WCMC

Data Quality: National protection only, does not include provincial or local protection

Other Notes: Areas of at least 1,000 hectares each; limited extractive use permitted

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Indicator: Totally protected areas (IUCN categories I - III) as a percentage of total area

Rationale: Measures amount of totally protected land

Year: 1994

Data Source: WCMC

Data Quality: National protection only, does not include provincial or local protection

Other Notes: Areas of at least 1,000 hectares each; limited extractive use permitted

---

Indicator: Forest remaining since pre-agricultural times (%)

Rationale: Measures amount of forest habitat remaining since pre-agricultural times

Year: 1980s

Data Source: WCMC and over 100 smaller studies

Data Quality: These data were abstracted by WRI from over 100 different sources, most of which used satellite imagery to assess vegetation cover. Because of the large number of sources, scales of measurement and definitions of "natural" habitat differ across studies. The pre-agricultural extents of habitats are estimated from potential vegetation maps. These maps are based on predictions made from current physical characteristics and may be error-prone.

Other Notes: None

Indicator: Average Annual Change in Forest Cover (%) (1981-90)

Rationale: Measures current rate of forest destruction (increase in forest is positive; decrease in forest is negative)

Year: 1990

Data Source: Food and Agriculture Organization of the United Nations (FAO)

Data Quality: Some definitional issues mean that developing and developed countries are not strictly comparable. However, the differences are considered by WRI to be "slight" (World Resources Institute et al 1998) (p. 222). In particular, in developed countries, plantations are included in the forested area, whereas in developing countries, plantations are considered separately. Since this analysis uses "all forest" data (summing natural forest and plantations), these definitional differences are minimized. Developed country data are considered high quality. For developing countries, Asia is considered the best quality, then Latin America, and lastly Africa.

Other Notes: FAO used a model to adjust the baseline forest inventory to a common year. However, the adjustment procedure for some types of forest (e.g., dry forest) are of unknown reliability.

3.6 Potential Confounders

The following indicators may modify or confound the EI - human health relationship.

Indicator: Carbon dioxide emissions per capita and carbon dioxide emissions per 1,000 hectares

Rationale: Surrogate for air quality and for industrialization

Year: 1992

Data Source: Carbon Dioxide Information Analysis Center (Oak Ridge National Laboratory, USA)

Data Quality: Uniform source; estimated to be within 10% of actual emissions; calculated from United Nations Statistical Division statistics, not from individual country governments (World Resources Institute et al 1998) (p. 332)

Other Notes: None

Indicator: Percentage of population living in urban areas

Rationale: Measures the percentage of the population living in highly disturbed areas

Year: 1995

Data Source: United Nations Population Division (UNPD)

Data Quality: Based on the midyear population of areas defined as urban by each country. The definition of urban may vary slightly from country to country. Numbers are based on population census. Accuracy varies, but the UN Population Division evaluates census and survey data and adjusts for over- or under-enumeration, as well as changes in definitions when necessary.

Other Notes: None

Indicator: Human population per square kilometer

Rationale: Measures crowding and density (assumption: that higher human density has a greater impact on land)

Year: 1995

Data Source: UNPD

Data Quality: Based on midyear populations obtained from census and surveys. Accuracy varies, but the UN Population Division evaluates census and survey data and adjusts for over- or under-enumeration, as well as changes in definitions when necessary.

Other Notes: None

Indicator: GDP per capita (Purchasing Power Parity (PPP)) ($Int)

Rationale: Measure of wealth that takes into account cost of living

Year: 1993

Data Source: World Bank

Data Quality: Data have been standardized to the United Nations System of National Accounts. However, there are some technical problems that are not easily resolved. WRI suggests that the data characterize major economic differences and not precise measurements.

Other Notes: Standardized by PPP to International dollars of purchasing power, not to exchange rates. The PPP is defined as "the number of units of a country's currency required to buy the same amount as $1 would buy in the "average" country" (World Resources Institute et al 1998) (p. 171).

Indicator: Gini Index

Rationale: Measure of income disparity

Year: Various

Data Source: Deininger and Squire (1997)

Data Quality: Deininger and Squire selected countries for a "high-quality" data set if they met the following inclusion criteria: national coverage, clear reference to the primary source, based on the entire population (i.e., not on the income earning population only or derived from non-representative tax records).

Other Notes: The Gini Index measures distribution of income on a scale of 1 to 100. A score of 100 indicates that all of the income is earned by a single individual and a score of 1 indicates that income is perfectly evenly distributed.

Indicator: Adult male literacy (%)

Rationale: Surrogate for educational level

Year: 1994

Data Source: United Nations Educational Scientific and Cultural Organization (UNESCO)

Data Quality: Although UNESCO has a recommended definition of literacy (see below), actual interpretation and application of the definition still varies from country to country. Also, most data were extrapolated from 1990 literacy data to 1994 population data; thus, changes in the proportion of the population that is literate after 1990 are not reflected.

Other Notes: The recommended definition for literacy is "a person who cannot with understanding both read and write a short, simple statement about his or her everyday life."

3.7 Indicators of Health

Because there is no certainty as to specific disease outcomes that might be important for diminishing EI, each of our indicators of health is an attempt to capture the general health of the population.

Indicator: Life expectancy at birth (5-year average)

Rationale: Measure of general health

Year: 1990-1995

Data Source: United Nations Population Division (UNPD)

Data Quality: Unknown, probably similar to other statistics obtained from UNPD

Other Notes: Average number of years that a newborn is expected to live if current age-specific mortality rates apply throughout the child's lifetime

---

Indicator: Infant Mortality Rate (5-year average) per 1,000 live births

Rationale: Measure of general health

Year: 1990-1995

Data Source: UNPD

Data Quality: Unknown, probably similar to other statistics obtained from UNPD

Other Notes: Infant mortality per 1,000 live births is the probability of dying by exactly age 1 multiplied by 1,000

Indicator: Percent of low birth weight babies

Rationale: Measure of general health

Year: 1990

Data Source: United Nations Children's Fund (UNICEF) and the World Health Organization (WHO)

Data Quality: Unknown

Other Notes: Refers to the percentage of babies who weigh less than 2,500 grams at birth. The 2,500 gram weight has been adopted as a standard international minimum by WHO.

In addition to the above variables, we also attempted to obtain disability-adjusted life year (DALY) data for our study, but were unsuccessful. The most complete source of DALY data provides DALYs attributable to specific illnesses aggregated across the eight WHO regions (Murray and Lopez 1996). At this time, however, country-level studies are in progress and may be expected in the next 5-10 years (personal communication between C. L. Soskolne and A. D. Lopez).

3.8 Country Inclusion and Exclusion Criteria

All countries for which data were available were considered for inclusion. This data set has already been screened by the source agencies; hence, some data points have already been excluded for various reasons. Sometimes, a data point may be indicated by the original source as unreliable. Those observations were excluded. A further exclusion criterion would be multiple entries per country. This occurs when countries have undergone name changes, or have split into smaller units. We endeavoured to include only the most modern country-name variants. However, some exceptions may occur if the data on the newest variant are sparse. One reason for the selection of several indicators of both EI and health is that if data were not available for a particular indicator, we were sometimes able to use another available measure in place of the missing indicator to boost sample size. Examples of countries excluded because of split data owing to name and territory changes include the former Yugoslavia and the former Soviet Union.

3.9 Analytical Method

Univariate analysis of all variables was conducted and appropriate data transformations applied. Transformations were necessary if the data were very skewed. An example of such a transformation is presented in Figure 3.9.1. When transformation was required, log to the base 10 was used. A further approach to transforming the data was to divide each of the variables by the potential confounder GDP per capita. This was unsuccessful, so, as mentioned, the log transformation was applied where deemed necessary.

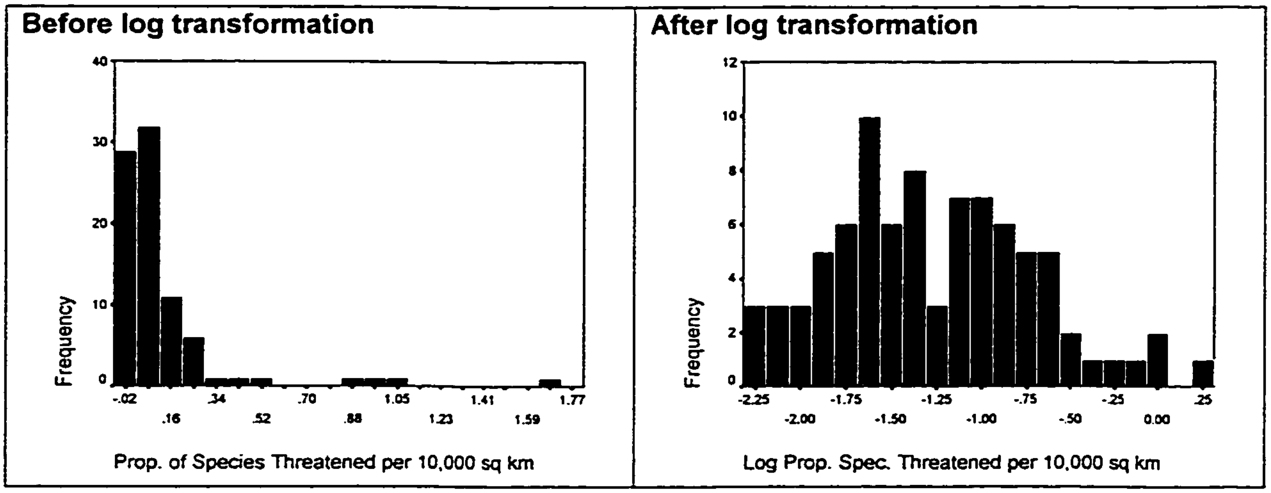

Figure 3.9.1 Example of Log Transformation of a Skewed Variable.

Bivariate scatterplots, categorical analysis, and correlation matrices were used to determine the relationships between pairs of variables, and to identify the most likely candidates for multiple regression.

Multivariate analysis was conducted by multiple linear regression (Briggs, Corvalan, and Nurminen 1996; Corvalan, Nurminen, and Pastides 1996). Several types of multiple regression were carried out as needed, including linear, robust, and non-linear models in an attempt to find the best fit for the data. Significance testing was generally avoided owing to the uncertain nature of "statistical significance" in a study in which the data are based on populations and not on samples. The underlying assumptions of each model were examined using appropriate diagnostic methods, which are described more fully in the context of the results in section 4.9. Also in Chapter 4, we provide added-variable plots (Mosteller and Tukey 1977) for each of our three outcomes. These provide not only a graphical representation of the relationship between a predictor and an outcome adjusted for the other variables in the model, but also allow us to detect outliers which may have undue influence on our regression slope coefficients.

The statistical methods outlined above are in line with suggested methods for aggregate data analysis described mainly by Morgenstern (Morgenstern 1982) (Greenland and Morgenstern 1989) and accepted by the World Health Organization (WHO) (Briggs, Corvalan, and Nurminen 1996; Corvalan, Nurminen, and Pastides 1996).

3.10 Statistical Formulae and Implementation

3.10.1 Pearson product-moment pair-wise correlation coefficient

A correlation matrix of all of the variables in the study is presented in Results section 4.7.1. Correlation matrices were used to determine the relationships between pairs of variables, and to identify the most likely candidates for multiple regression. The pair-wise correlations were calculated using the formula by Galton (Galton 1888):

$$\rho = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \sqrt{\sum (y_i - \bar{y})^2}}$$

3.10.2 Cuzick test for trend

The Cuzick test was used as a contrast with the pair-wise correlations to see if the continuous relationships provided by the correlation matrix were consistent with “cruder” categorical comparisons. This test is a Wilcoxon-type test for trend modified with a correction for ties (Cuzick 1985). A mathematical explanation of the test is given by

Altman (Altman 1991). It is implemented in Stata 5.0 (StataCorp 1997) as -nptrend- (Stepniewska and Altman 1992).

In essence, this is a z-test given by:

$$z = \frac{T - E(T)}{se(T)}$$

The test is illustrated by a simple example. Consider three groups: short, medium, and tall. Each of these groups is given a constant, c_i, which reflects its order. For example, c(short) = 1, c(medium) = 2, and c(tall) = 3. Assume that each group has 3 individuals giving a total sample size, N, of 9. We rank each of the 9 individuals from lowest to highest according to something else that we are interested in measuring, say weight. The sum of the ranks in each group is R. The formula for T above is:

$$T = \sum c_i R_i$$

where c_i is the group ordering constant (1, 2, or 3 in this example) and R_i is the sum of the ranks in the *i*th group. Thus, the largest value of T is obtained when the lowest ranks are multiplied by the lowest ordering constant and the highest ranks are multiplied by the highest ordering constant. This can only occur in this example when the lighest people are also the shortest and the heaviest people are the tallest. A large T is then reflected as a low p-value indicating that, for this example, there is a trend from lighter to heavier with increasing height.

3.10.3 Multiple linear regression

Multiple linear regression was carried out using ordinary least squares according to the usual model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j + \varepsilon$$

where the x_i are variables, β_i are parameters, and ε is the error term.

It is implemented in Stata 5.0 using the -fit- command, which allows the calculation of subsequent diagnostics (StataCorp 1997).

3.10.4 Variance inflation factors

After the estimation of a multiple linear regression model using Stata's -fit- command, variance inflation factors (VIFs) (Chatterjee and Price 1991) can help to determine the degree of collinearity among the predictors.

$$\mathrm{VIF}(x_j) = \frac{1}{1-R_j^2}$$

where R^2 is the coefficient of determination from the regression of x_j on all other explanatory variables. Thus, a low VIF results from a low R^2. A low R^2 is obtained when the other predictors are not highly correlated with x_j. In other words, the VIF is low when x_j is not collinear with the other predictors in the model. It is implemented after Stata's -fit- command as -vif-.

3.10.5 Cook-Weisberg test for heteroscedasticity

Once a multiple linear regression model was estimated, we tested for heteroscedasticity using the Cook-Weisberg test (Cook and Weisberg 1983).

$\mathrm{Var}(e_i) = \sigma^2 \exp(z_i t)$

where e_i is the ith residual, $z = (z_1, z_2, \ldots, z_j)$ is the vector of fitted values, and t is a constant. The test is for whether $t = 0$. If $t = 0$, then $\exp(z_i t) = 1$. This would mean that the variance of the residuals is equal to the overall variance and heteroscedasticity is not present. It is implemented after Stata's -fit- command as -hettest-.

3.10.6 Robust multiple linear regression

Ordinary least squares regression can yield unsatisfactory results when influential outliers are present. Robust regression performs better under these conditions. The form of robust regression implemented in Stata's -rreg- command is explained here (Hamilton 1992).

In robust regression, outliers are assigned lower weights, thus lessening their influence on the final coefficients. The outliers are weighted gradually so that the further out the case lies, the lower its weight will be. Because of the use of weights, this method is a form of weighted least squares regression. The weights derive from complicated weight functions which are beyond the scope of this thesis to explain. To ensure that weights are appropriately calculated for all outliers, Stata implements two weight functions: first Huber weights (Huber 1964) and then biweights (Beaton and Tukey 1974).

Chapter 4 - Results

4.1 Univariate Analysis – Indicators of EI

The un-transformed univariate distributions of our indicators of EI are shown in Figures 4.1.1 through 4.1.6.

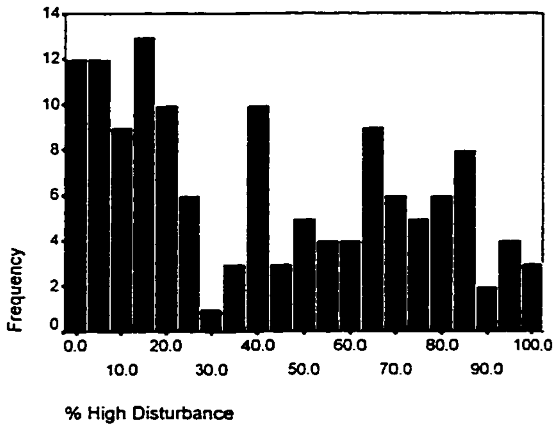

Figure 4.1.1 Univariate distribution (histogram) of percent of land highly disturbed by human activity.

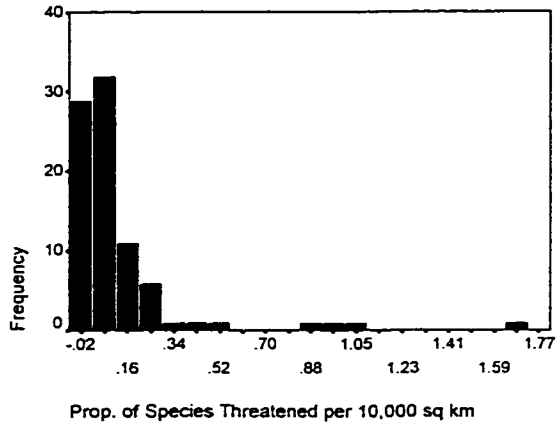

Figure 4.1.2 Univariate distribution of proportion of species threatened per 10,000 sq km.

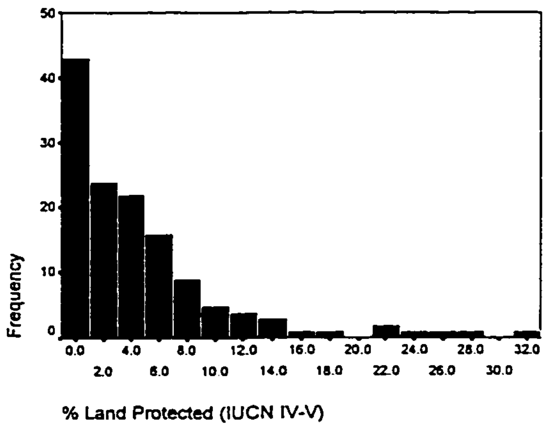

Figure 4.1.3 Univariate distribution of percent of land totally protected (IUCN categories IV-V).

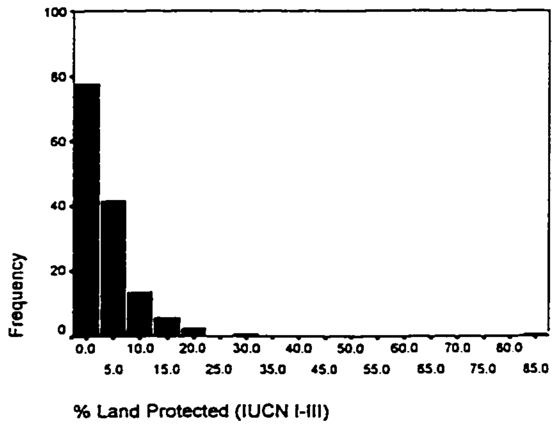

Figure 4.1.4 Univariate distribution of percent of land partially protected (IUCN categories I-III).

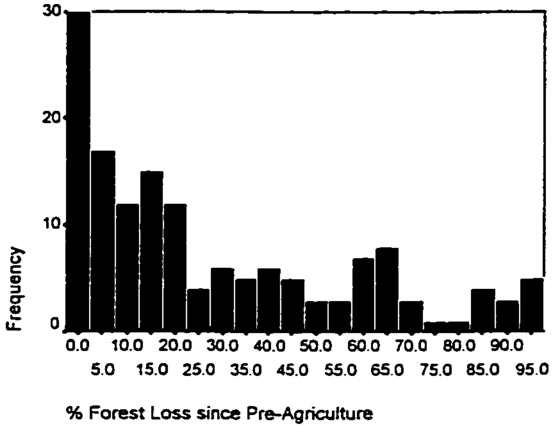

Figure 4.1.5 Univariate distribution of percent forest remaining since pre-agricultural times.

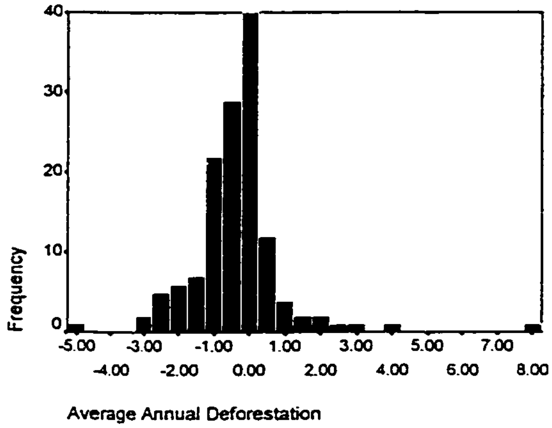

Figure 4.1.6 Univariate distribution of average percent annual change in forest cover.

4.2 Univariate Analysis – Log Transformations of Indicators of EI

As can be seen in Figures 4.1.2, 4.1.3, and 4.1.4, the distributions of some of the EI variables are highly skewed. The Pearson product-moment correlations to be calculated in the bivariate analysis require all variables to be approximately normally distributed. It should be noted that subsequent linear regression modeling does not require that the independent variables need be normal, but it is desirable for them to have a reasonable spread. For both of these reasons, log (base 10) transformations were taken of the extremely skewed variables to render them suitable for linear modeling. In general, we wanted to work with variables that were in their natural units and therefore only the most skewed of the variables were transformed. The distributions after log transformation are shown in Figures 4.2.1 through 4.2.3 for those variables for which log transformation was deemed necessary. One can see from Figures 4.2.1 through 4.2.3 that these variables now have reasonable spread.

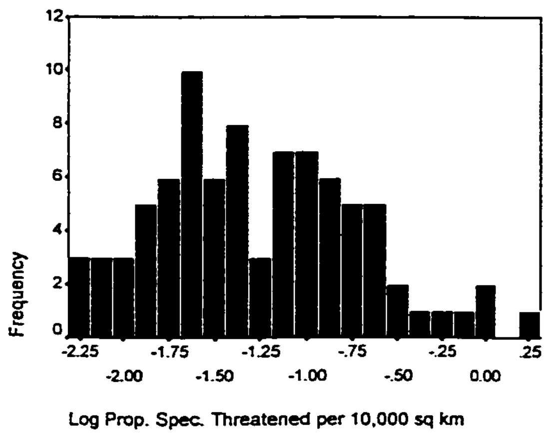

Figure 4.2.1 Univariate distribution of proportion of species threatened per 10,000 sq km (log_{10} transformation).

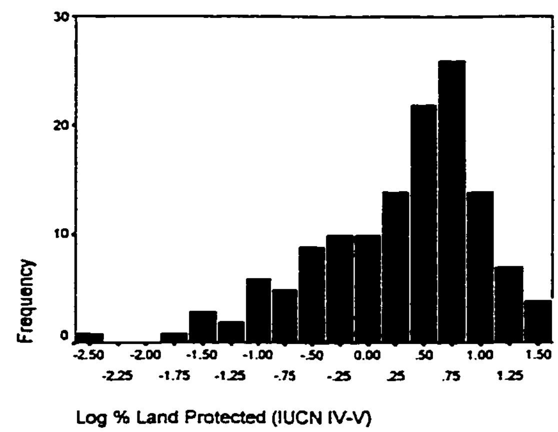

Figure 4.2.2 Univariate distribution of percent of land totally protected (IUCN categories IV-V) (log_{10} transformation)

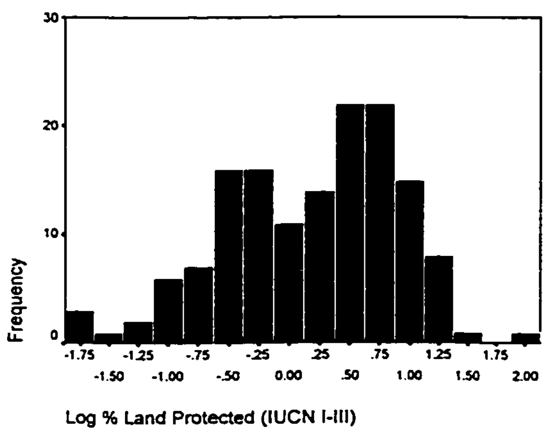

Figure 4.2.3 Univariate distribution of percent land partially protected (IUCN categories I-III) (log_{10} transformation).

4.3 *Univariate Analysis – Potential Confounders*

The un-transformed univariate distributions of our potential confounders are shown in Figures 4.3.1 through 4.3.7.

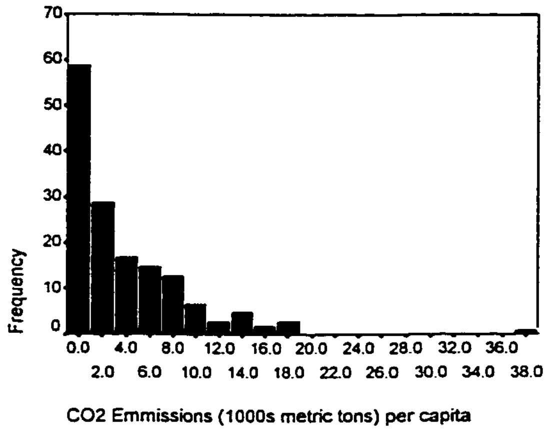

Figure 4.3.1 Univariate distribution of CO_2 emissions per capita.

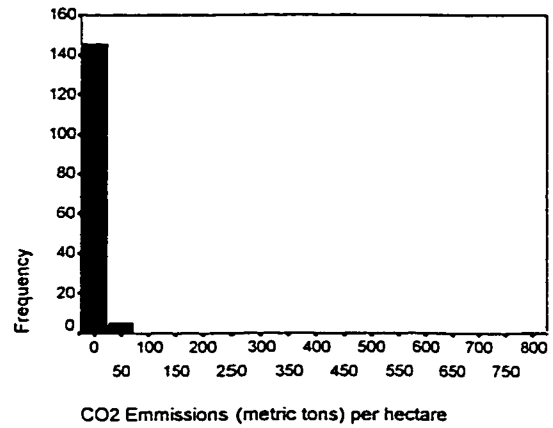

Figure 4.3.2 Univariate distribution of CO_2 emissions per hectare.

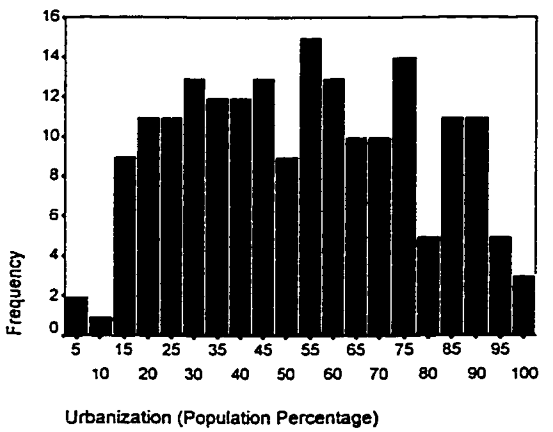

Figure 4.3.3 Univariate distribution of percent of population living in urban areas.

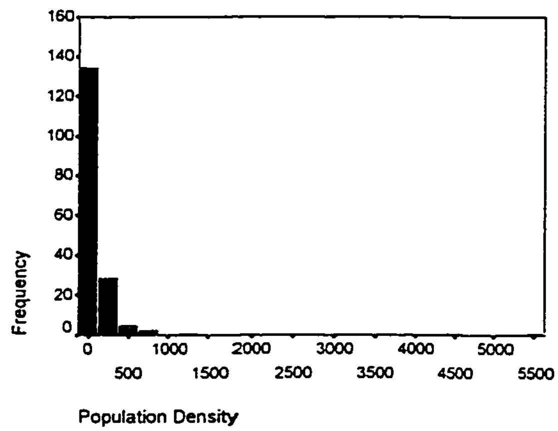

Figure 4.3.4 Univariate distribution of human population per square kilometer.

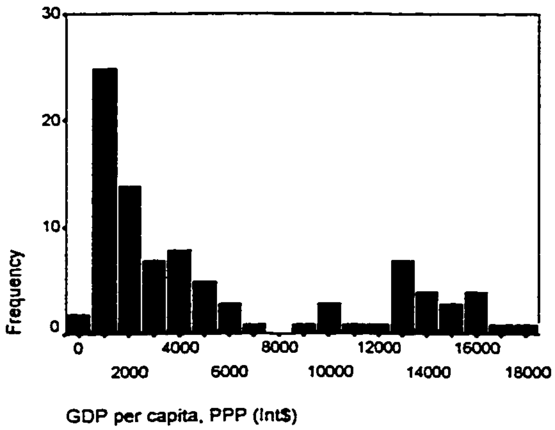

Figure 4.3.5 Univariate distribution of GDP per capita (Purchasing Power Parity)

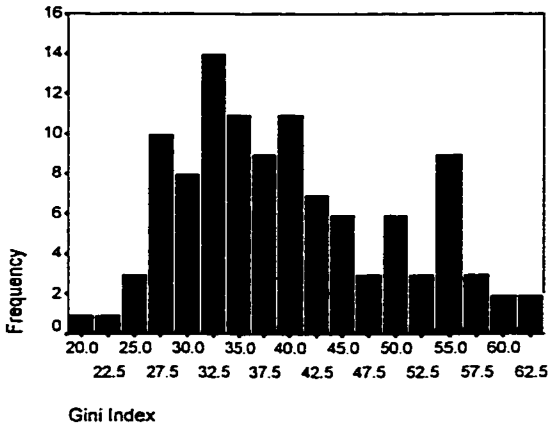

Figure 4.3.6 Univariate distribution of the Gini Index.

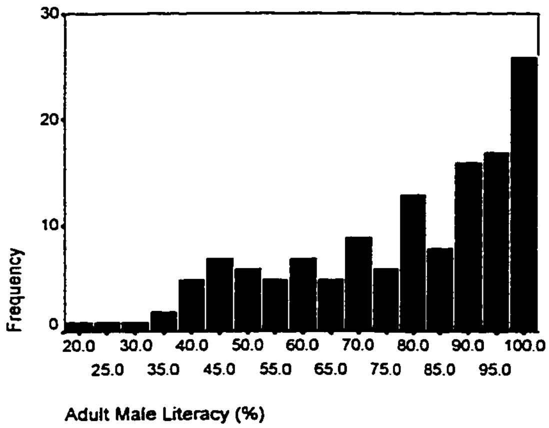

Figure 4.3.7 Univariate distribution of percent adult male literacy.

4.4 Univariate Analysis – Log Transformations of Potential Confounders

Figures 4.3.1, 4.3.2, 4.3.4, and 4.3.5 are quite skewed and so the respective variables were transformed using log base 10 for the same reasons given in section 4.2. The transformed variables are shown in Figures 4.4.1 through 4.4.4 and are now quite well spread.

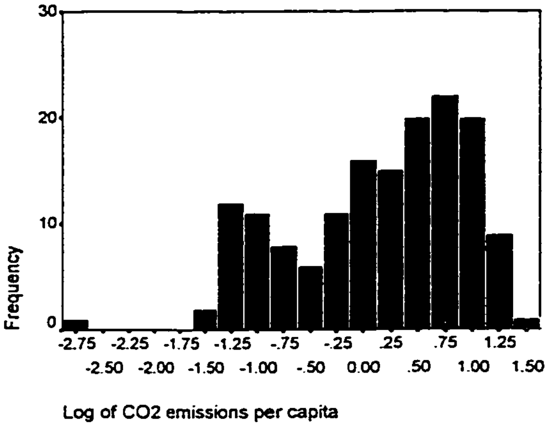

Figure 4.4.1 Univariate distribution of CO_2 emissions per capita ($\log_{10}$ transformation).

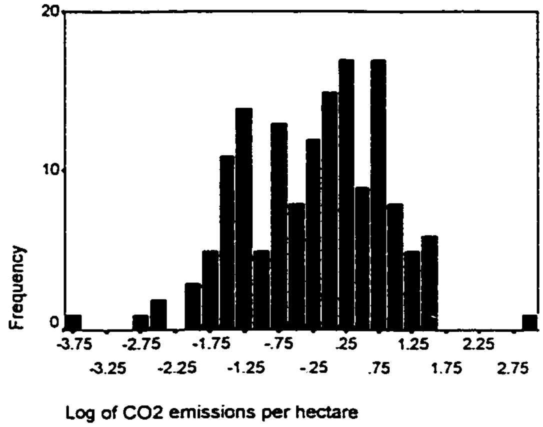

Figure 4.4.2 Univariate distribution of CO_2 emissions per hectare ($\log_{10}$ transformation).

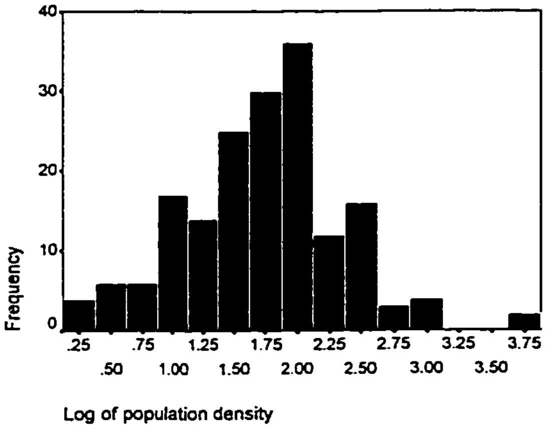

Figure 4.4.3 Univariate distribution of human population per sq km ($\log_{10}$ transformation).

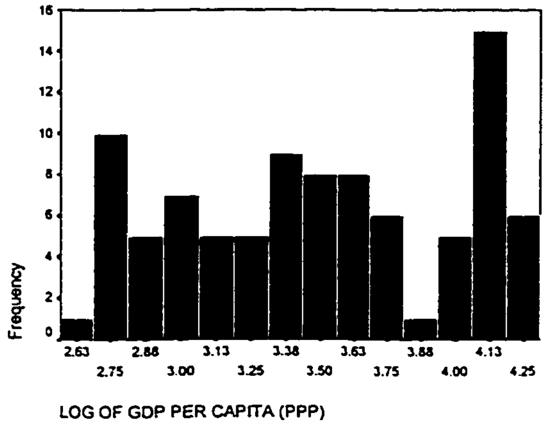

Figure 4.4.4 Univariate distribution of GDP per capita (PPP) ($\log_{10}$ transformation)

4.5 Univariate Analysis – Indicators of Health

The un-transformed univariate distributions of our indicators of health are shown in Figures 4.5.1 through 4.5.3.

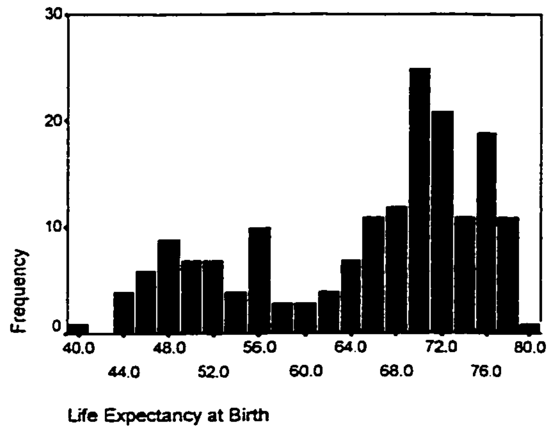

Figure 4.5.1 Univariate distribution of life expectancy at birth (5-year average).

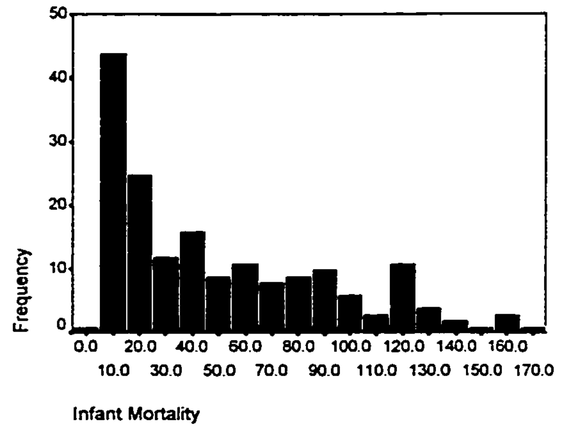

Figure 4.5.2 Univariate distribution of infant mortality rate – 5 year average (per 1,000 live births).

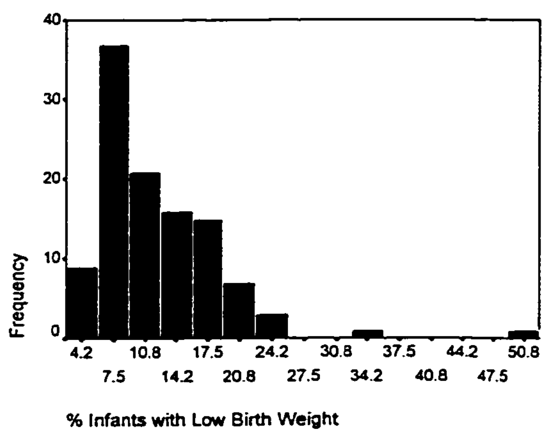

Figure 4.5.3 Univariate distribution of percent of live births that are low birth weight (<2,500 grams).

4.6 Univariate Analysis – Log Transformation of Indicators of Health

Extreme skewness in the outcome variables violates the assumption of normality of the dependent variable in linear regression. It can be seen from Figures 4.5.2 and 4.5.3 that the distribution of infant mortality and low birth weight are not normal. They have been transformed to their base 10 logs and the new distributions are shown in Figures 4.6.1 and 4.6.2. They are now much more approximately normal than before the transformations.

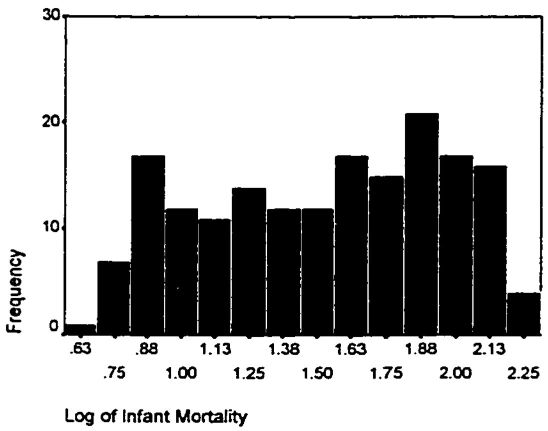

Figure 4.6.1 Univariate distribution of infant mortality per 1,000 live births (log_{10} transformation).

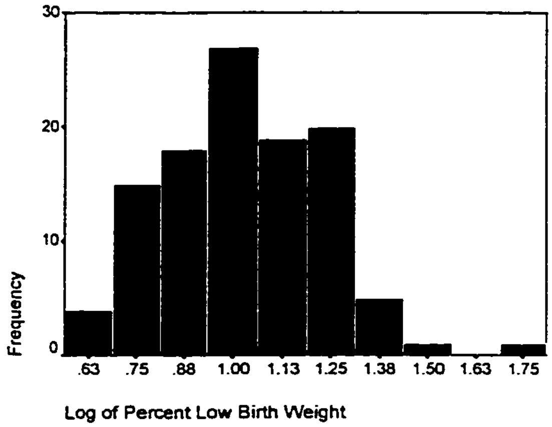

Figure 4.6.2 Univariate distribution of percent of live births with low birth weight (<2,500 grams) (log_{10} transformation).

4.7 Selection of Covariates for Multiple Regression

We used all of the above indicators of EI and potential confounders in our multiple regression modeling. However, the order in which variables are entered into the model can make a difference in the final model selected. Therefore, we wanted to identify the most important variables so that we could enter them first. We used several procedures to help determine which variables were best related to our outcomes, and thus which should first be entered into the multiple regression models.

4.7.1 Correlation matrix

The first tool we used was a correlation matrix (Pearson product-moment correlations described in Materials and Methods section 3.10.1) to determine the relative magnitude of the associations between not only our predictors and our outcomes, but also to assess the associations (collinearity) between our predictors. The entire correlation matrix was rather large, and so it was broken into smaller parts for readability. The parts of the matrix are provided in Tables 4.7.1 through 4.7.3.

Table 4.7.1 Pearson correlations among indicators of EI and all other variables (* means p<0.1).

	high disturbance	species threatened (log)	IUCN IV-V protected (log)	IUCN I-III protected (log)	forest remaining	annual change in forest
high disturbance	1.000					
species threatened (log)	-0.126	1.000				
IUCN IV-V protected (log)	0.224 *	-0.042	1.000			
IUCN I-III protected (log)	-0.043	0.079	0.116	1.000		
forest remaining	-0.196 *	0.139	0.084	0.290 *	1.000	
annual change in forest	0.015	0.084	0.040	-0.296 *	-0.119	1.000
CO_2 emissions per cap. (log)	0.164 *	0.076	0.214 *	-0.158 *	0.144 *	0.215 *
CO_2 emissions per hec (log)	0.533 *	0.004	0.263 *	-0.154 *	-0.061	0.151 *
urbanization	0.112	0.003	0.160 *	-0.091	0.094	0.159 *
population density (log)	0.709 *	-0.090	0.160 *	-0.074	-0.334 *	-0.014
GDP (PPP) (log)	0.210 *	0.017	0.384 *	-0.029	0.323 *	0.154
Gini index	-0.326 *	0.194	-0.204 *	0.343 *	0.121	-0.374 *
adult male literacy	0.192 *	0.215 *	0.075	-0.004	0.284 *	0.040
life expectancy	0.311 *	0.120	0.252 *	-0.028	0.174 *	0.099
infant mortality (log)	-0.374 *	-0.027	-0.356 *	-0.004	-0.146 *	-0.150 *
low birth weight (log)	-0.187 *	0.028	-0.246 *	0.072	-0.173 *	-0.286 *

Table 4.7.1 gives the Pearson correlations among the indicators of EI and the three categories of study variables; indicators of EI, potential confounders, and health outcomes, which are separated by dotted lines. The EI variables are largely uncorrelated.

Similarly, the potential confounders are mostly uncorrelated with the EI variables with the exception of log CO_2 emissions per hectare and log population density, which are correlated with high disturbance (r = 0.533 and 0.709, respectively). While the entire table is of interest, the main function of this table is to help us choose predictors of our health outcomes. Thus, the most important part of the table is the bottom three rows which provide the correlations among the EI variables and the health outcomes. None of the correlations in this section are large (maximum = -0.374), indicating that the EI variables are not good predictors of health outcomes. It indicates that high disturbance and log IUCN IV-V protected areas are the two strongest predictors, in terms of magnitude, of both life expectancy and log infant mortality. For log low birth weight, log IUCN IV-V protected areas and percent change in forests seem to be the strongest predictors. We consider a correlation coefficient of 0.7 or higher to represent significant inter-correlation. If two predictors are more than approximately 70% correlated, then we prefer not to include both in the regression model owing to the potential for collinearity.

Table 4.7.2 provides the Pearson correlations among the potential confounders and between the potential confounders and the health outcomes. It is useful because it indicates which of our potential covariates are most highly inter-correlated as well as those that might be important predictors of the health outcomes. We note that log carbon dioxide emissions per capita and log carbon dioxide emissions per hectare are highly correlated (r = 0.820). This is not very surprising, but it does indicate that it would be prudent to include only one or the other in our final model.

In addition, it is striking that log GDP per capita is very highly correlated with everything except the Gini Index (with which it retains a quite strong correlation of -0.423) and log population density. This, perhaps, is not surprising since many of these potential confounders are related to the general idea of socio-economic "development". It makes intuitive sense that socio-economic development and wealth would be strongly related. It will be shown below that because GDP per capita is such an important and overwhelming variable, we decided to treat it differently than all of the other variables.

However, not only is GDP per capita strongly inter-related with most of the other variables, correlation coefficients are high to very high among most of the other confounders. This indicates that the inclusion of these potential confounders in the final regression models must be undertaken judiciously to avoid problems with collinearity.

We can also see that all of these potential confounders are significantly predictive of our outcomes: life expectancy, infant mortality, and low birth weight. The one exception is that population density does not appear to be strongly related to low birth weight.

Table 4.7.2 Pearson correlations among potential confounders and indicators of health (* means p<0.1).

	CO_2 per capita (log)	CO_2 per hectare (log)	urbanization	population density (log)	GDP (PPP) (log)	Gini index	adult male literacy
CO2 emissions per cap. (log)	1.000						
CO2 emissions per hec (log)	0.820 *	1.000					
urbanization	0.784 *	0.643 *	1.000				
population density (log)	0.063	0.620 *	0.128 *	1.000			
GDP (PPP) (log)	0.927 *	0.761 *	0.815 *	0.121	1.000		
Gini index	-0.379 *	-0.471 *	-0.201 *	-0.242 *	-0.423 *	1.000	
adult male literacy	0.702 *	0.616 *	0.539 *	0.134	0.696 *	-0.085	1.000
life expectancy	0.824 *	0.765 *	0.699 *	0.262 *	0.900 *	-0.320 *	0.780 *
infant mortality (log)	-0.792 *	-0.766 *	-0.711 *	-0.304 *	-0.934 *	0.419 *	-0.741 *
low birth weight (log)	-0.742 *	-0.553 *	-0.677 *	-0.016	-0.790 *	0.266 *	-0.572 *

Table 4.7.3 Pearson correlations among indicators of health (* means p<0.1).

	life expectancy	infant mortality (log)	low birth weight (log)
life expectancy	1.000		
infant mortality (log)	-0.905 *	1.000	
low birth weight (log)	-0.775 *	0.821 *	1.000

Table 4.7.3 gives the Pearson correlations among our three health outcomes. It indicates that our outcomes are highly correlated with one another. Of course, separate regression models will be fit for each of the outcomes; hence, collinearity is not of concern when modeling these variables.

Much could be conjectured from these correlation matrices. However, it is important to remember that they represent only bivariate relationships. The large correlation coefficients between many of the predictors is indicative that confounding could be important, and therefore, not too much weight should be placed on these bivariate results. Multiple regression is required to sort out the true relationships among these variables.

4.7.2 Categorical comparisons

Linear regression and correlation make use of continuous data to generate slope coefficients. In the case of unweighted regression and correlation, the assumption is made that each data point can be treated equally with regard to data quality. Our data, however, are derived from multiple sources and they attempt to cover vast areas of the globe with unknown precision. Thus, we undertook a seemingly more "crude" analysis in which we divided each outcome into quintiles from lowest to highest. Then we called the lowest fifth the "low" category and the highest fifth the "high" category. The intent was to isolate the extremes. We combined the middle three fifths and called it the "medium" category. Then, we compared the mean values of each predictor across these broad categories of the outcomes. These gross differences may be more easily defensible in light of the unknown accuracy and precision of our data.

Differences between the ordered groups were tested using a modified non-parametric Wilcoxon test for trend (Cuzick 1985). An explanation for this test is provided in Materials and Methods section 3.10.2.

Tables 4.7.4 through 4.7.6 provide the mean, number of observations, and p-values of the Cuzick test for each predictor and each outcome.

The results of these categorical analyses are not very different from those of the correlation matrices in terms of p-values. Of course, p-values are not the best way to compare results because they confound sample size and magnitude of association. Further, the Cuzick test is a test for trend, so its p-value could be low simply because of a large difference between any two of the categories, and not necessarily because of a generally strong relationship between the predictor and outcome. However, this does provide a non-parametric counterpart to the correlation coefficients provided earlier. It has the advantage of relying on fewer distributional assumptions. In general, then, it can be said that when the correlation coefficient has a low p-value, the Cuzick test also returned a low p-value. In the prediction of life expectancy (Table 4.7.4) and infant mortality (Table 4.7.5), all variables are significant except log species threatened and IUCN I-III protected areas, with forest remaining being marginally so. In the prediction of low birth weight, fewer of the variables are significant with log species threatened, IUCN I-III protected areas, and log population density being the least so. Also, variables that appeared to be of some importance in the prediction of life expectancy and infant mortality, high disturbance and forest remaining, are marginally associated with low birth weight.

Table 4.7.4 Categorical analysis: means and p-values of all predictors across categories of life expectancy.

	Life Expectancy at Birth						
	Low		Medium		High		P-value
	Mean	n	Mean	n	Mean	n	Cuzick
high disturbance	26.12	35	39.97	71	60.25	26	0.00
species threatened (log)	-1.47	8	-1.25	53	-1.21	23	0.45
IUCN IV-V protected (log)	0.20	26	0.07	76	0.73	29	0.00
IUCN I-III protected (log)	0.26	28	0.11	86	0.17	26	0.45
forest remaining	22.01	35	31.32	86	32.11	27	0.12
annual change in forest	-0.47	36	-0.50	75	0.11	22	0.00
CO_2 emissions per cap. (log)	-0.88	35	0.29	92	0.90	27	0.00
CO_2 emissions per hec (log)	-1.46	35	-0.04	91	0.75	27	0.00
urbanization	29.43	37	53.12	103	76.08	35	0.00
population density (log)	1.43	37	1.71	103	2.01	35	0.00
GDP (PPP) (log)	2.90	16	3.36	46	4.10	26	0.00
Gini index	43.27	19	40.86	61	34.72	27	0.00
adult male literacy	53.67	36	84.43	87	93.27	11	0.00

Table 4.7.5 Categorical analysis: means and p-values of all predictors across categories of infant mortality.

	Infant Mortality (per 1,000 live births)						
	Low		Medium		High		P-value
	Mean	n	Mean	n	Mean	n	Cuzick
high disturbance	62.11	25	37.12	75	30.68	32	0.00
species threatened (log)	-1.21	21	-1.23	54	-1.51	9	0.35
IUCN IV-V protected (log)	0.75	30	0.08	78	0.13	23	0.00
IUCN I-III protected (log)	0.16	27	0.14	89	0.20	24	0.63
forest remaining	32.80	25	30.71	91	22.39	32	0.13
annual change in forest	0.23	22	-0.53	78	-0.47	33	0.00
CO_2 emissions per cap. (log)	0.92	28	0.26	94	-0.96	32	0.00
CO_2 emissions per hec (log)	0.81	28	-0.10	93	-1.50	32	0.00
urbanization	75.20	37	52.71	104	28.58	35	0.00
population density (log)	2.04	37	1.67	104	1.47	34	0.00
GDP (PPP) (log)	4.12	25	3.37	47	2.87	16	0.00
Gini index	33.78	29	41.80	60	41.83	19	0.00
adult male literacy	95.70	10	83.27	91	53.58	33	0.00

Table 4.7.6 Categorical analysis: means and p-values of all predictors across categories of low birth weight.

	Percent of Babies with Low Birth Weight						
	Low		Medium		High		P-value
	Mean	n	Mean	n	Mean	n	Cuzick
high disturbance	54.10	28	33.82	59	39.80	20	0.13
species threatened (log)	-1.18	23	-1.16	37	-1.16	7	0.86
IUCN IV-V protected (log)	0.57	28	0.05	53	-0.02	15	0.01
IUCN I-III protected (log)	0.03	25	0.22	55	0.05	14	0.63
forest remaining	30.83	29	30.32	59	15.02	20	0.12
annual change in forest	0.01	22	-0.76	58	-0.69	20	0.00
CO_2 emissions per cap. (log)	0.86	29	-0.05	58	-0.77	20	0.00
CO_2 emissions per hec (log)	0.70	29	-0.46	58	-1.01	20	0.00
urbanization	73.05	29	50.56	61	25.48	20	0.00
population density (log)	1.84	29	1.62	61	1.76	20	0.43
GDP (PPP) (log)	4.05	21	3.37	38	2.96	14	0.00
Gini index	34.12	24	45.59	44	39.42	12	0.01
adult male literacy	90.46	13	76.28	58	58.05	20	0.00

There are additional analyses that could be done at this bivariate stage, including the graphing of the bivariate distributions of all of the variables. This might allow us to determine the strength and the functional form of the relationships between predictors and outcomes, but these relationships would likely change once they were considered in the light of multiple regression with its ability to mutually adjust all covariates for one another. Thus, additional bivariate steps would add little additional knowledge to what we have learned from correlation matrices and categorical comparisons. Therefore, we used these bivariate techniques only in helping to obtain an initial picture of which variables are likely to be important in multiple regression modeling. More sophisticated analyses were postponed until the multivariate stage.

4.8 *Multivariate Analysis – Model Building Strategy*

All models were built manually in stages; no automated stepwise procedure was used. The first stage involved finding the best combination of indicators of EI, including in this first stage those indicators of EI that were statistically significant and/or added significantly to the R^2 value and/or significantly influenced the coefficients in the model by its inclusion. The second stage was to add the other potential confounders into the model using the same criteria as the first stage. The final stage was to eliminate those covariates whose presence did not significantly affect the R^2 value or the other coefficients in the model. Only main effects were considered. The result of this modeling style is a parsimonious model containing only the important covariates.

Early in the model building process, we realized that the addition of GDP per capita into the multivariate model caused all other covariates to lose significance. Its presence overwhelmed the contributions of all of the other covariates. We concluded that GDP was in some way a surrogate for all of the other predictors in the model. Essentially, we had a model in which all of our covariates were either correlated with GDP per capita, or in the causal pathway. Our data, being cross-sectional population-based averages, can not distinguish between correlation and causation. We had to treat GDP per capita in a special way; instead of including it in the multivariate model, we stratified our final model by categories of GDP per capita.

All model building was carried out using Stata 5.0's -fit- command (StataCorp 1997), which performs multiple linear regression and stores important parts of the hat matrix in macros to allow for subsequent diagnostic analysis.

4.9 Multivariate Analysis – Life Expectancy as Outcome

This section describes an analysis with life expectancy as outcome. A main effects model was reached containing two indicators of integrity, high disturbance and original forest remaining, and two other covariates, log CO_2 emissions per capita and urbanization. Table 4.9.1 provides the coefficients and characteristics for this model.

Table 4.9.1 Main effects model with life expectancy as outcome.

No. of obs = 127		R^2 = 0.7595				
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
forest remaining	0.038	0.018	0.036	0.002	0.073	0.098
high disturbance	0.067	0.016	0.000	0.035	0.099	0.191
CO_2 emissions per cap. (log)	8.233	0.992	0.000	6.268	10.197	0.621
urbanization	0.097	0.033	0.004	0.031	0.163	0.215
constant	54.489	1.980	0.000	50.570	58.408	

The model has a high R^2 value of 0.7595, indicating that the predictors in the model explain about 76% of the variance in life expectancy. The two non-EI covariates, log CO_2 emissions per capita (R = 0.621) and urbanization (R = 0.215), are stronger predictors than the indicators of EI.

We have indicated before that the reason for accounting for GDP per capita by stratification, rather than by including it as a predictor in our regression models, is that it was so overwhelming. For illustrative purposes, we provide in Table 4.9.2 the main effects model in Table 4.9.1 with the addition of log GDP per capita. In Table 4.9.3, we provide the model with log GDP per capita as the sole predictor of life expectancy. Notice that the R^2 value is very high in the GDP per capita-only model and that it is not very different from the R^2 value for the model with the other predictors. Not having a useful R^2 value that can differentiate between models would have made modeling with GDP per capita very difficult and uncertain.

Table 4.9.2 Main effects model with life expectancy as outcome and log GDP per capita added for illustrative purposes.

No. of obs = 108	R^2 = 0.8188					
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
forest remaining	-0.005	0.023	0.839	-0.050	0.041	-0.012
high disturbance	0.006	0.022	0.800	-0.039	0.050	0.016
CO_2 emissions per cap. (log)	0.886	2.050	0.667	-3.200	4.972	0.061
urbanization	0.017	0.045	0.705	-0.072	0.106	0.036
GDP per capita (log)	18.490	3.493	0.000	11.529	25.451	0.819
constant	-0.315	10.754	0.977	-21.746	21.117	

Table 4.9.3 Model with life expectancy as outcome and log GDP per capita as the sole predictor (for illustrative purposes).

No. of obs = 108	R^2 = 0.8098					
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
GDP per capita (log)	19.601	1.024	0.000	17.565	21.637	0.900
constant	-2.958	3.614	0.415	-10.142	4.226	

One of our concerns in this model is the presence of collinearity between log CO_2 emissions per capita and urbanization. The correlation between percent urbanization and log CO_2 emissions per capita is 0.7840, which is quite highly correlated. However, Chatterjee and Price (Chatterjee and Price 1991) suggest calculating variance inflation factors (VIF) (formula and explanation in Materials and Methods section 3.10.4) and assessing collinearity using two rules of thumb. First, if the largest VIF is greater than 10, and second, if the mean of all VIFs is much larger than 1, then there is a strong probability of collinearity in the model and the variable with the largest VIF should be removed. Table 4.9.4 indicates that it is safe to keep both log CO_2 emissions per capita and urbanization in the model.

Table 4.9.4 Variance inflation factors of model covariates (life expectancy as outcome).

Variable	VIF
CO_2 emissions per cap. (log)	2.85
urbanization	2.74
forest remaining	1.1
high disturbance	1.08
Mean VIF	1.94

In order to check for the presence of omitted variables in the model, we constructed a residual-versus-fitted plot. The residual-versus-fitted plot (see Figure 4.9.1) is used to search for a pattern in the residuals that might be indicative of an omitted variable. Aside from a couple of outliers, the residual-versus-fitted plot for this model appears quite random, suggesting little, if any, pattern in the residuals.

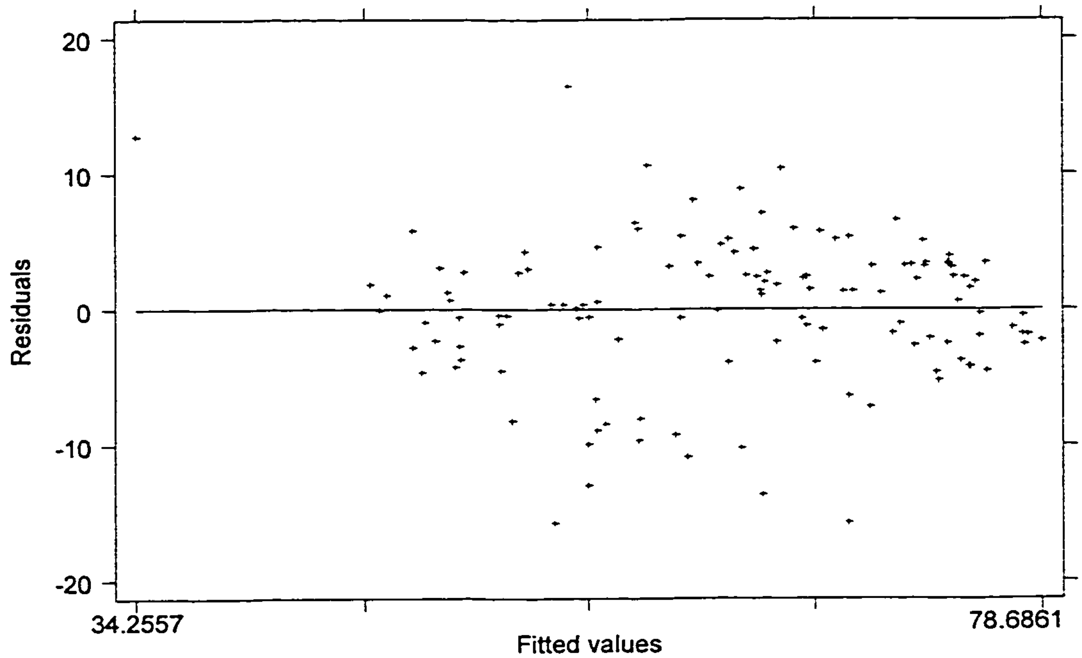

Figure 4.9.1 Residual-versus-fitted plot for main effects model predicting life expectancy.

A second concern is to determine if, in fact, the simple linear term in the model appropriately reflects the correct functional form of the variable in the model. One way to determine the correct functional form for each predictor in a multivariate model is to graph a component-plus-residual plot, also called a partial residual plot (Larsen and McCleary 1972). The component-plus-residual plot graphs the covariate residuals, duly adjusted for all of the other variables in the model, against the values of the covariate (a.k.a., the "component"). These plots should show that the data points conform to a generally linear arrangement about the regression line. Figures 4.9.2 through 4.9.5 are the component-plus-residual plots for this model. They indicate that the addition of non-linear terms would make very little difference to the final model. In each case, the functional form of covariate is easily defensible as being approximately linear, with several outliers. We will return to the issue of outliers below. Thus, the final model is unchanged and remains as shown in Table 4.9.1.

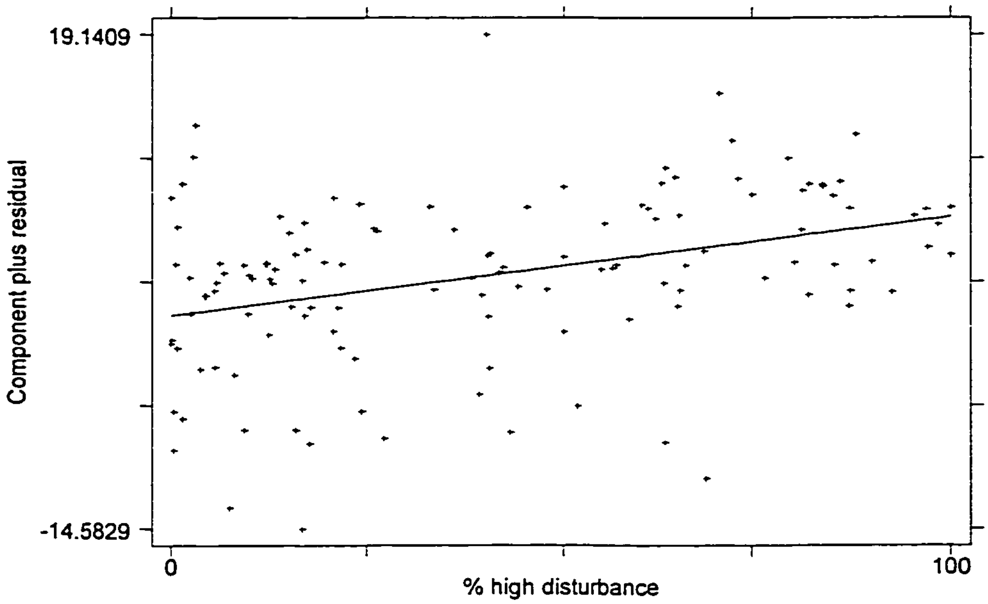

Figure 4.9.2 Component-plus-residual plot of high disturbance in life expectancy model.

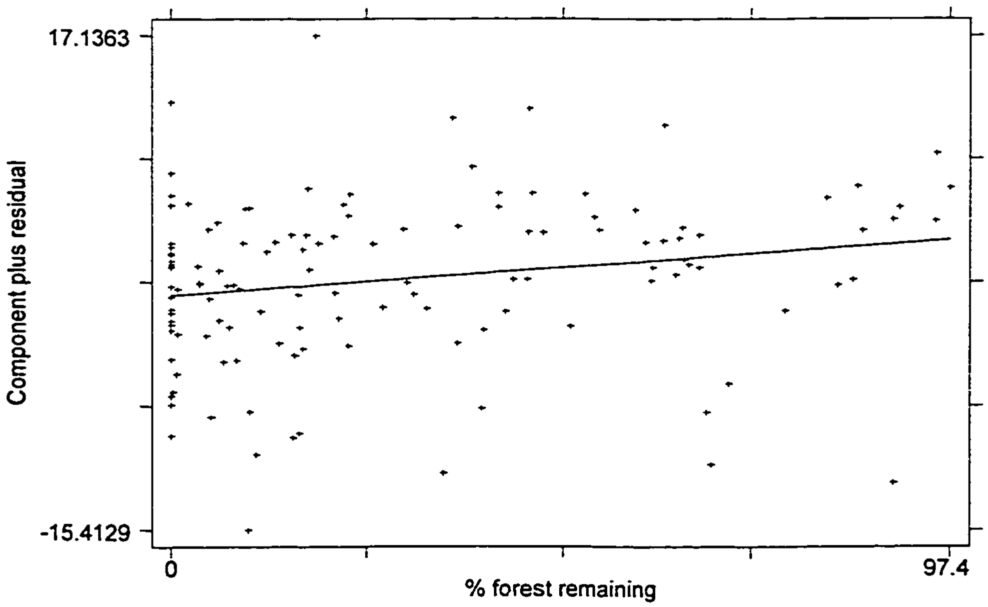

Figure 4.9.3 Component-plus-residual plot of forest remaining in life expectancy model.

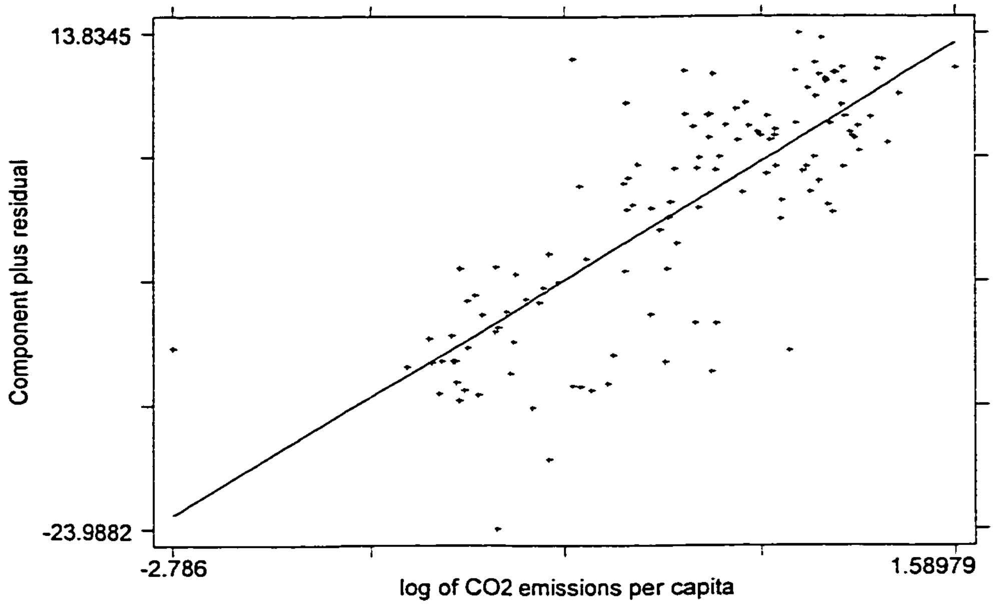

Figure 4.9.4 Component-plus-residual plot of log CO_2 emissions per capita in life expectancy model.

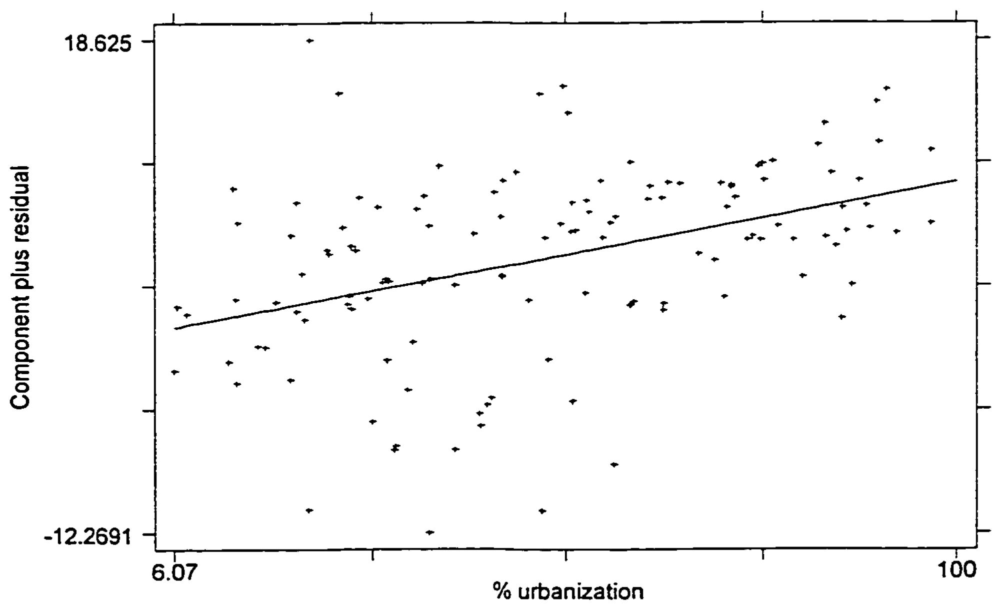

Figure 4.9.5 Component-plus-residual plot of urban in life expectancy model.

A further assumption of linear regression that we wish to test is that of constant variance. The values of the Cook-Weisberg test for heteroscedasticity are shown in Table 4.9.3. We reject the null hypothesis of constant variance if the p-value of the test is less than

0.05. The Cook-Weisberg test indicates that there is significant heteroscedasticity in both log CO_2 emissions per capita and urbanization, but not in the indicators of EI.

Table 4.9.5 P-values of the Cook-Weisberg test for heteroscedasticity – life expectancy outcome (Ho: constant variance).

Variable	p-value
CO_2 emissions per cap. (log)	0.034
urbanization	0.013
forest remaining	0.690
high disturbance	0.104

Based on the values of the Cook-Weisberg tests in Table 4.9.5, we want to visualize the heteroscedasticity of our variables. At the same time, we would like a general plot which would allow us to see the association between each predictor and the outcome, adjusting for the mutual covariance between the variable in question and all of the other variables in the model. A perfect plot of this is impossible since it would require a graph with n+1 dimensions (where n is the number of covariates). However, Mosteller and Tukey (Mosteller and Tukey 1977) suggest that most of this information can be compressed into a two-dimensional graph of adjusted residuals called an added-variable plot. Figure 4.9.6 displays all four added-variable plots for this model, one for each covariate in the model.

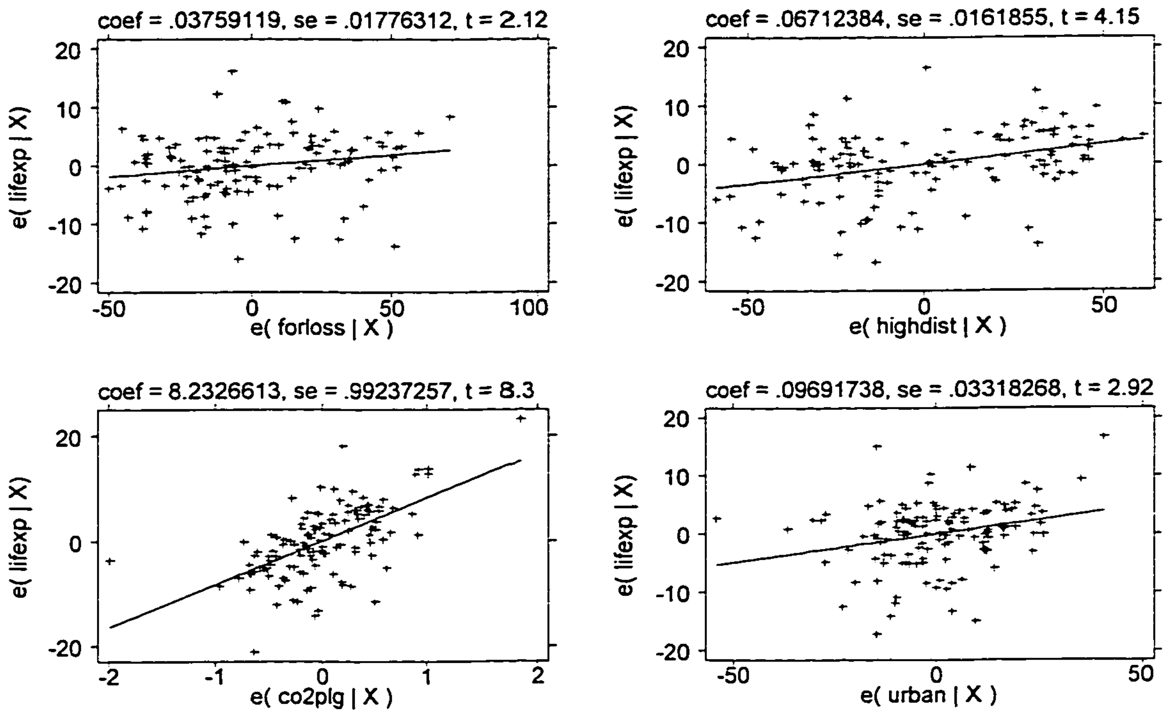

Figure 4.9.6 Added-variable plots of each variable in the life expectancy model.

These plots indicate that the heteroscedasticity alluded to by the Cook-Weisberg tests appears to be caused mainly by a few outliers, and appears relatively minor. Since this problem of outliers has occurred twice now, we conducted robust linear regression. In this procedure, each data point is weighted according to how far it falls from the regression line. Table 4.9.6 contains these estimates and reveals that some differences in the coefficients occur with robust regression (robust regression explained in Materials and Methods section 3.10.6) compared to ordinary least squares (OLS) linear regression, but nothing very important.

Table 4.9.6 Robust regression estimates for life expectancy model.

	Robust Regression					OLS
	Coef.	Std. Err.	p-value	95% Conf. Interv.		Coef.
forest remaining	0.052	0.016	0.002	0.020	0.084	0.038
high disturbance	0.068	0.015	0.000	0.038	0.097	0.067
CO2 emissions per cap. (log)	9.034	0.901	0.000	7.250	10.819	8.233
urbanization	0.071	0.030	0.020	0.012	0.131	0.097
constant	55.737	1.798	0.000	52.177	59.296	54.489

Earlier in this chapter, we alluded to the special manner in which we wish to treat GDP per capita as a variable. In particular, it will be recalled that the addition of GDP per capita into the multiple regression model causes the model to be entirely reduced to that single covariate. Nevertheless, owing to the importance of this variable, we found it necessary to deal with its association with life expectancy in some way. Therefore, we divided GDP per capita into low, medium, and high categories and then ran the main effects model within each of the GDP categories. That is, we built a single model for each outcome and then split the data across categories of GDP per capita. Ideally, we would have built separate models for each level of GDP. However, doing this would have meant building models having up to thirteen predictors and only about 30-40 data points. Building models on so few data points just did not seem appropriate. The cut-off points for the low, medium, and high categories were set according to those used in the World Bank Development report (World Bank. 1993). In this way, we should be able to see, indirectly, the associations between GDP per capita and the other covariates in predicting life expectancy.

To visualize this relationship, we fit our main effects model within each category of GDP per capita. We have found it more informative to show the stratified relationships using added-variable plots rather than in tabular format. Figures 4.9.7 through 4.9.10 show added-variable plots for each model covariate stratified across categories of GDP per capita. Each figure shows the relationship between a single covariate from the main effects model and life expectancy.

Figure 4.9.7 depicts three added-variable plots (one for each category of GDP per capita) of the association between high disturbance and life expectancy adjusted for the other independent variables in the model. It shows that the association is relatively weak (owing to the shallow slope of the regression line), and consistently positive (owing to the increasing slope), for all levels of GDP per capita. It also shows that the regression slopes decrease by an order of magnitude from the low GDP per capita category to the high GDP per capita category. There are some outliers, but none appear to be particularly influential on the slope of the regression line.

Figure 4.9.8 depicts three added-variable plots (one for each category of GDP per capita) of the association between percent original forest and life expectancy adjusted for the other independent variables in the model. It shows that the association is relatively weak among low-income countries, basically non-existent for middle-income countries, and quite strong among high-income countries. The most interesting outliers are in the low GDP per capita category with Mauritania, Guyana, and Zambia appearing to have significant influence on the slope of the regression line (the slope coefficient without these three countries is 0.023 compared to 0.050 with them included).

Figure 4.9.9 depicts three added-variable plots (one for each category of GDP per capita) of the association between log CO_2 emissions per capita and life expectancy adjusted for the other independent variables in the model. It shows that the association is strongly positive among low- and medium-income countries, and strongly negative among high-income countries. There are no unduly influential outliers among the low-income countries. Among the middle-income countries, Oman, Cameroon, and Senegal are influential outliers (the slope coefficient without these three countries is 2.105 compared to 5.938 with them included). Among the high-income countries, Iceland, the United States of America (USA) and the United Arab Emirates (UAE) appear to be influential outliers, but their removal does not change the slope coefficient substantially (the slope coefficient without these three countries is –3.75 compared to –3.44 with them included).

Figure 4.9.10 depicts three added-variable plots (one for each category of GDP per capita) of the association between urbanization and life expectancy adjusted for the other independent variables in the model. It shows that the association is weakly negative among low-income countries, weakly positive among medium-income countries, and strongly positive among high-income countries. Among the low-income countries, Nicaragua and Sierra Leone appear somewhat influential, however their removal does not substantially change the slope coefficient (-0.074 with Nicaragua and Sierra Leone included, -0.090 with them removed). Among the middle- and high-income countries, there are quite a number of outliers; however, they seem to approximately balance one another out.

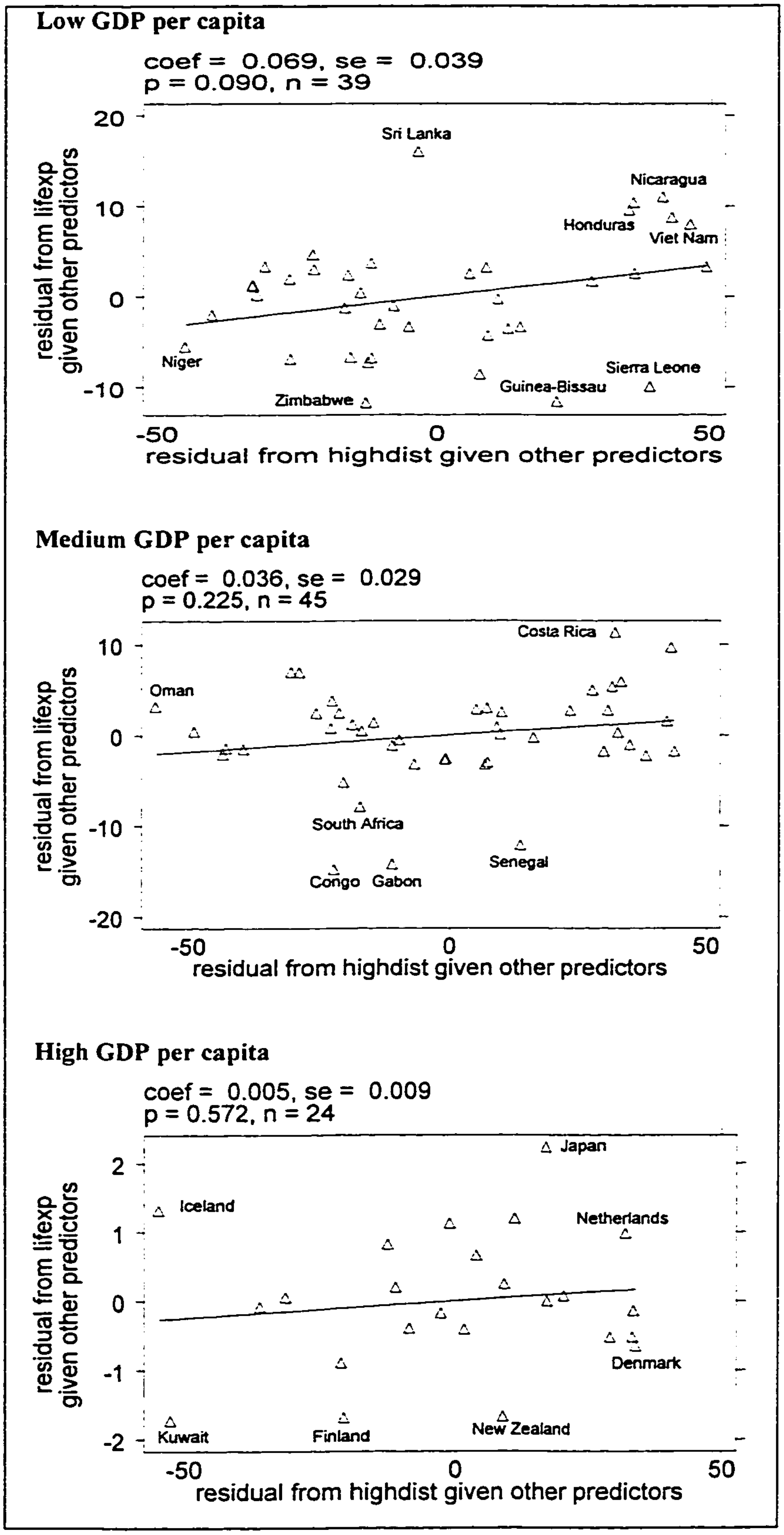

Figure 4.9.7 The association between high disturbance and life expectancy adjusted for model covariates and stratified by GDP per capita category.

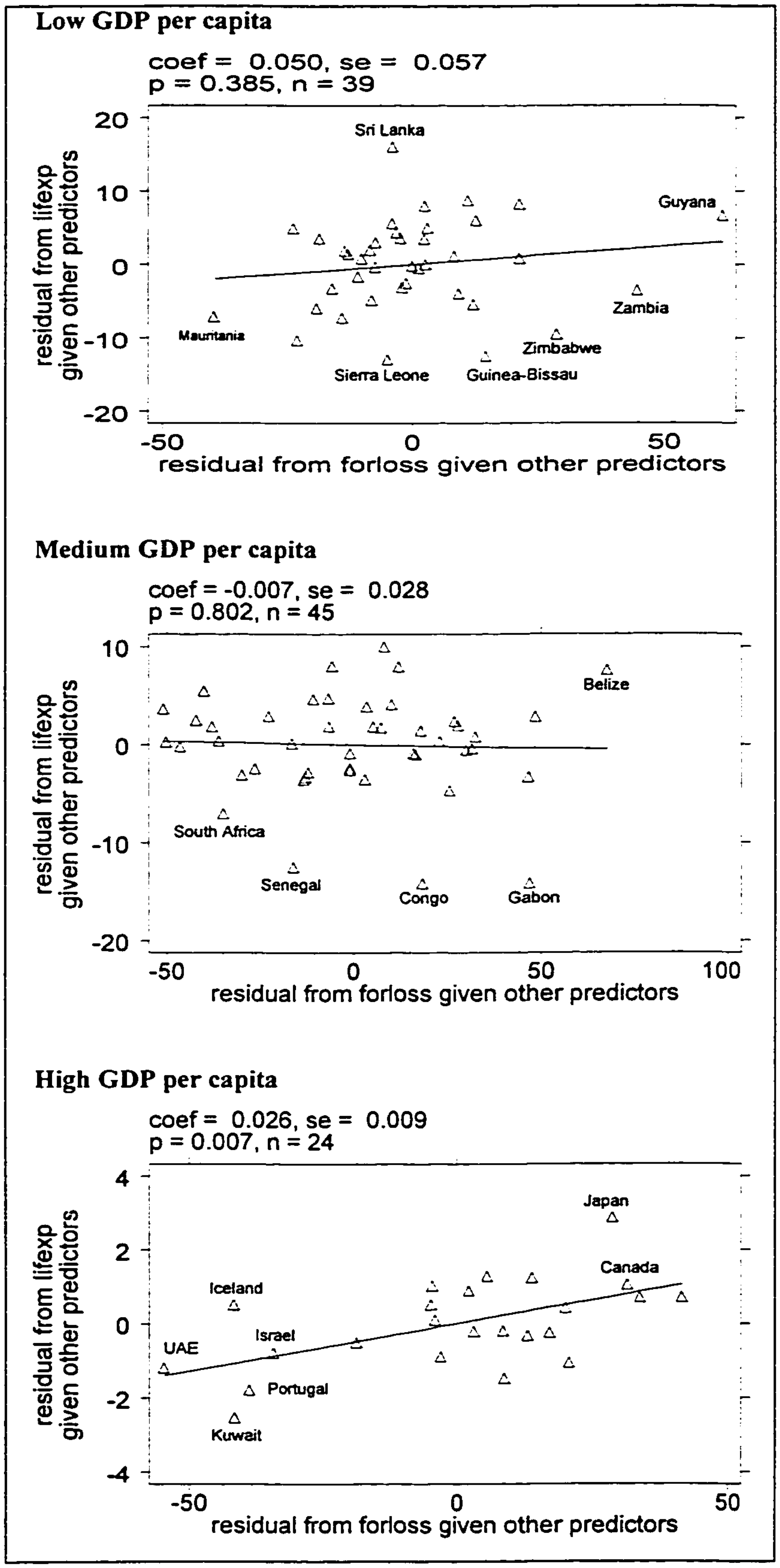

Figure 4.9.8 The association between % of original forest on life expectancy adjusted for model covariates and stratified by GDP per capita category.

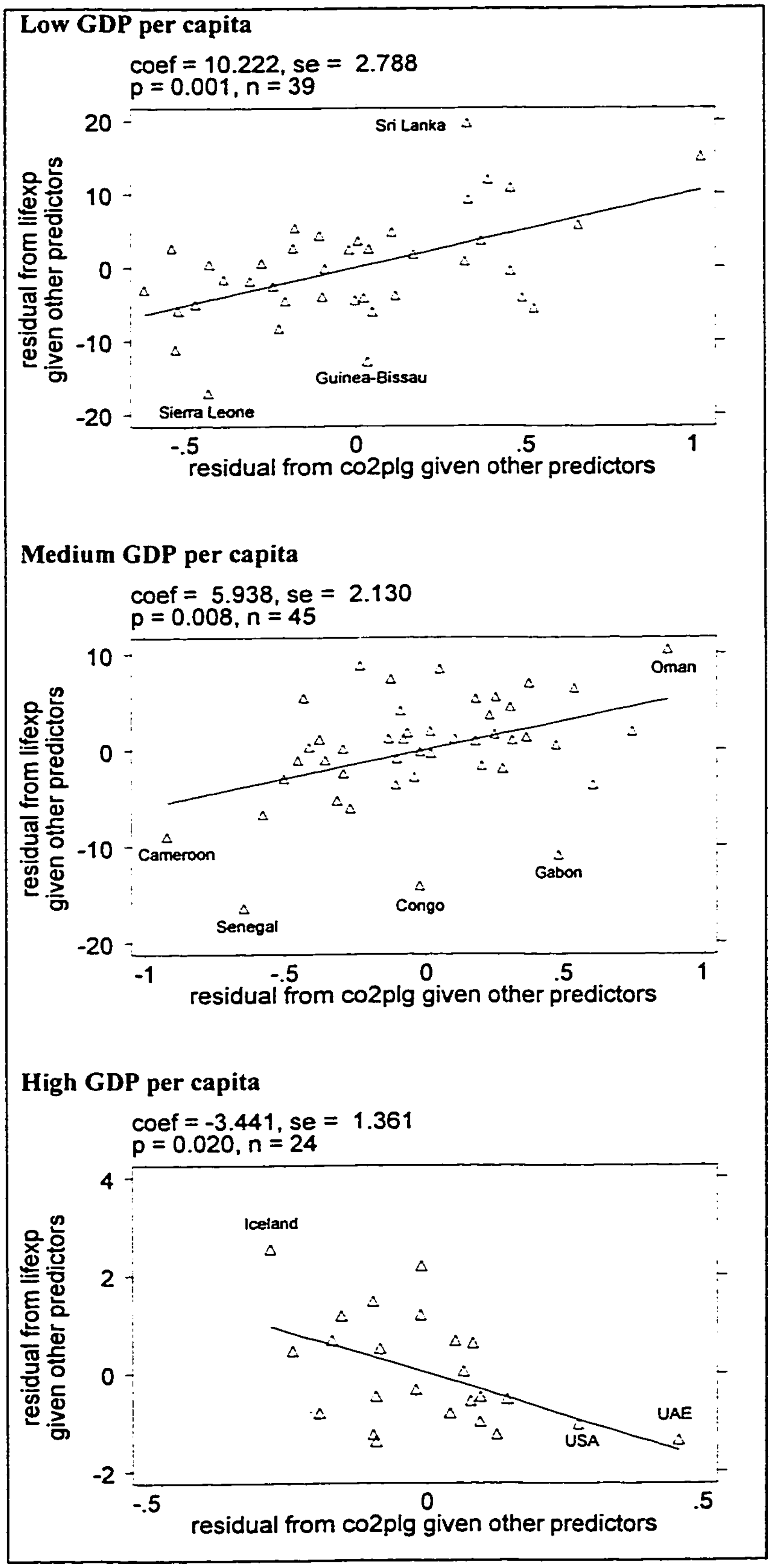

Figure 4.9.9 The association between log CO_2 emissions per capita and life expectancy adjusted for model covariates and stratified by GDP per capita category.

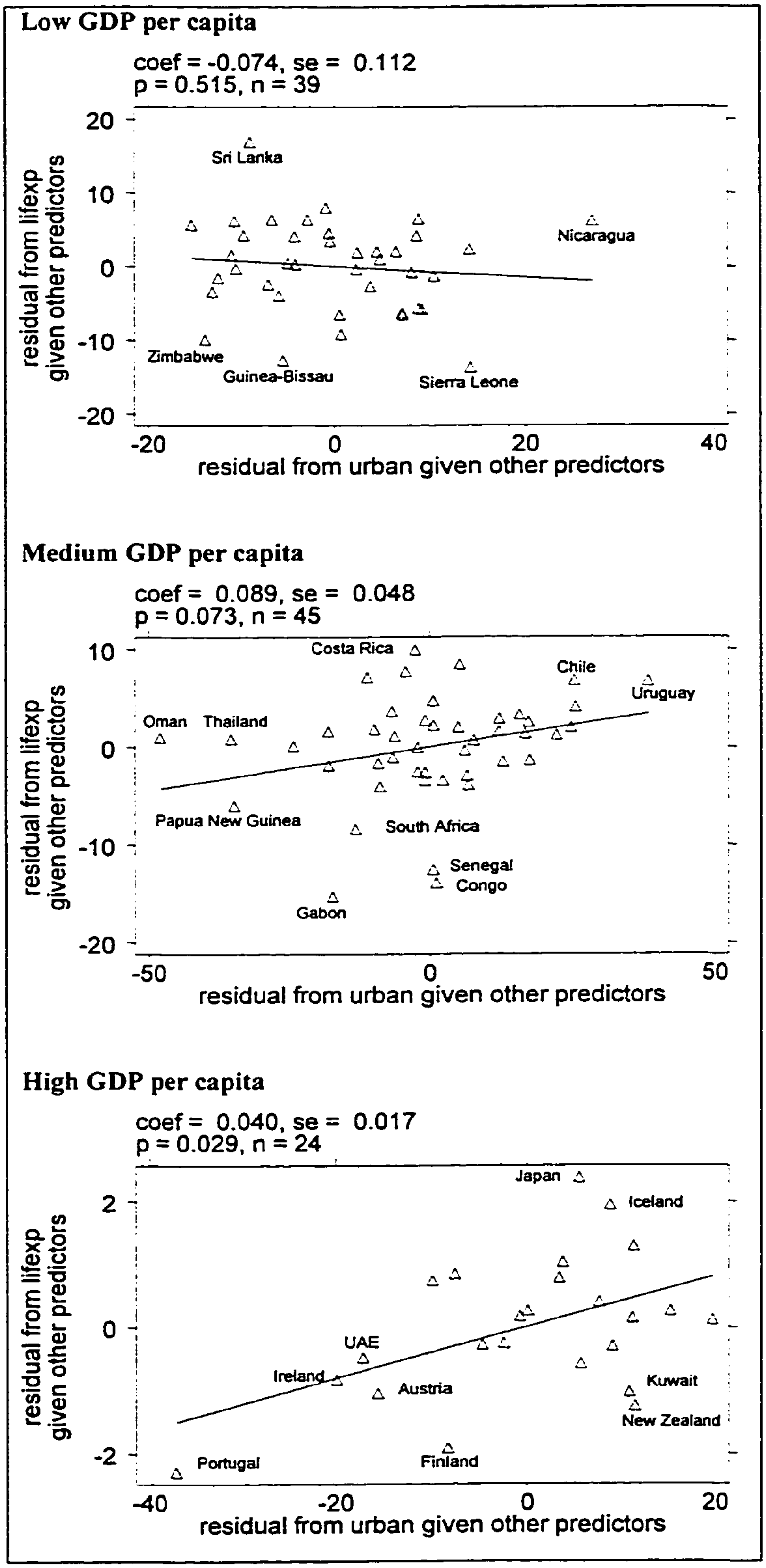

Figure 4.9.10 The association between urbanization and life expectancy adjusted for model covariates and stratified by GDP per capita category.

4.10 Multivariate Analysis – Infant Mortality as Outcome

The commentary that accompanied the results of the multivariate model with life expectancy was quite detailed and the reasoning behind each step was explained. In this section (4.10) and the next section (4.11), we present the results for the multivariate models with infant mortality and low birth weight as the respective outcomes. The results are presented in abbreviated form because the model building and testing processes already have been provided.

First, recall that we did not use infant mortality per se as the outcome, but rather the $\log_{10}$ of infant mortality. This was done only because the univariate distribution of infant mortality was strongly skewed to the right.

For the multivariate model with infant mortality as the outcome, we arrived at the same four covariates as for the life expectancy model, with one additional variable: the Gini Index. The similarity between this model and that with life expectancy as the outcome is perhaps not surprising given that the Pearson correlation between life expectancy and log infant mortality is 0.905.

Table 4.10.1 provides the coefficients and characteristics of the initial multivariate main effects model predicting infant mortality.

Table 4.10.1 Main effects model with log infant mortality as outcome.

No. of obs = 85	R^2 = 0.8025					
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
high disturbance	-0.003	0.001	0.001	-0.005	-0.001	-0.195
forest remaining	-0.002	0.001	0.041	-0.004	0.000	-0.120
CO2 emissions per cap. (log)	-0.341	0.057	0.000	-0.456	-0.227	-0.547
urbanization	-0.004	0.002	0.026	-0.007	0.000	-0.195
Gini index	0.009	0.003	0.001	0.004	0.014	0.194
constant	1.562	0.142	0.000	1.279	1.845	

The model has a high R^2 value of 0.8025, indicating that the predictors in the model explain about 80% of the variance in log infant mortality. As with the life expectancy model, log CO_2 emissions per capita (R = -0.547) and is the strongest predictor. The Gini Index and urbanization contribute approximately as much as the two indicators of EI.

As with the analysis using life expectancy as the outcome, the correlation matrix (see Figure 4.7.2) suggests a potential collinearity problem between log CO_2 emissions per capita and urbanization. We calculated the variance inflation factors (VIF) and present them in Table 4.10.2. The VIFs for this model indicate that collinearity is not likely to be influential in our results.

Table 4.10.2 Variance inflation factors of model covariates (log infant mortality as outcome).

Variable	VIF
CO2 emissions per cap. (log)	3.40
urbanization	2.92
high disturbance	1.34
forest remaining	1.33
Gini index	1.22
Mean VIF	2.04

The residual-versus-fitted plot in Figure 4.10.1 does not indicate a random distribution, indicating that we have a misspecified model. As will be seen presently, the addition of a quadratic term to the model results in a residual-versus-fitted plot with a more random distribution.

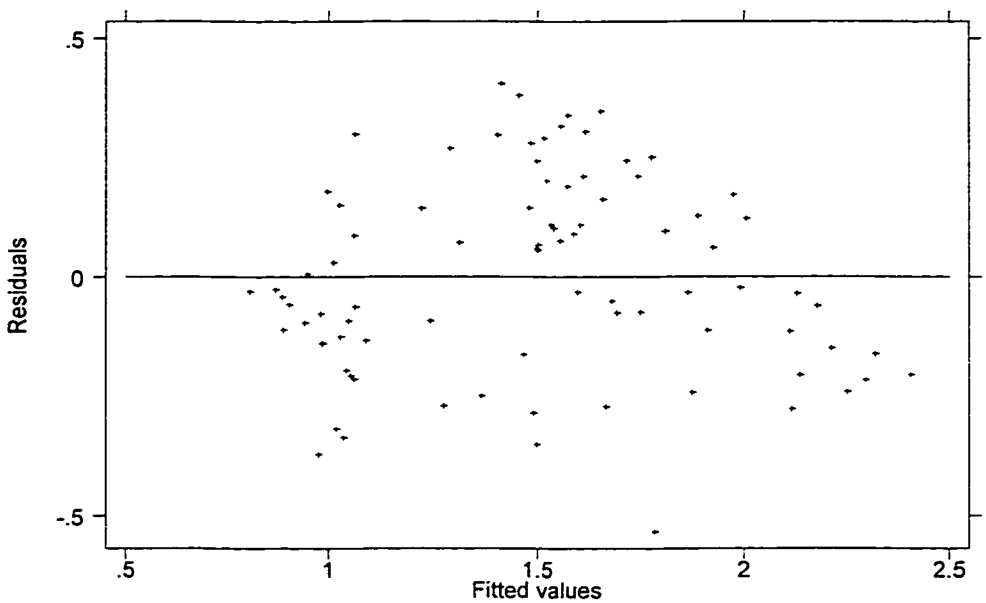

Figure 4.10.1 Residual-versus-fitted plot for main effects model predicting log infant mortality.

To check for the correct functional form of each of our covariates, Figures 4.10.2 through 4.10.6 display the component-plus-residual plot for each model covariate. In these plots, we are checking to see that each plot suggests an approximately linear fit.

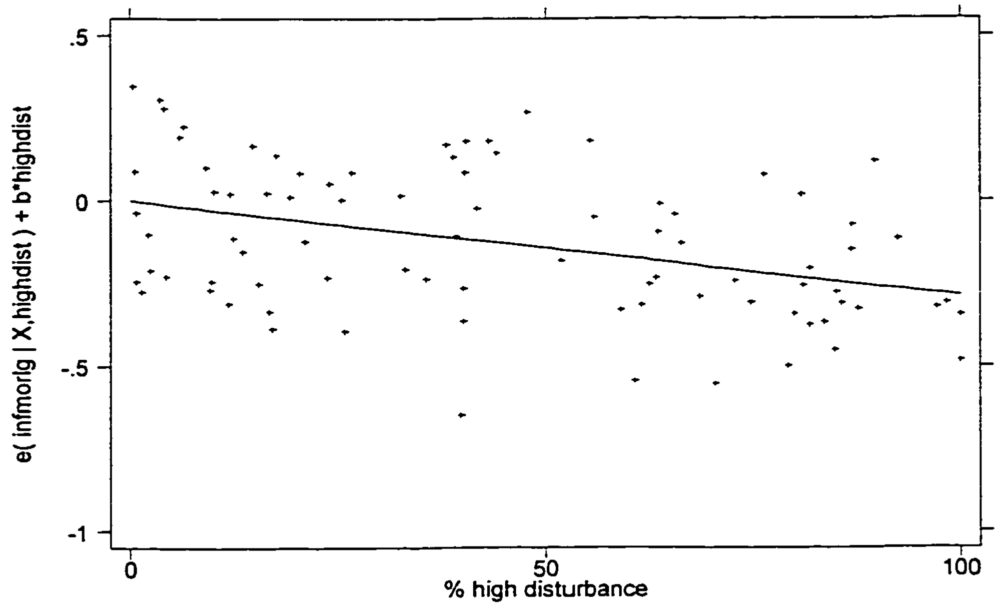

Figure 4.10.2 Component-plus-residual plot of high disturbance in log infant mortality model.

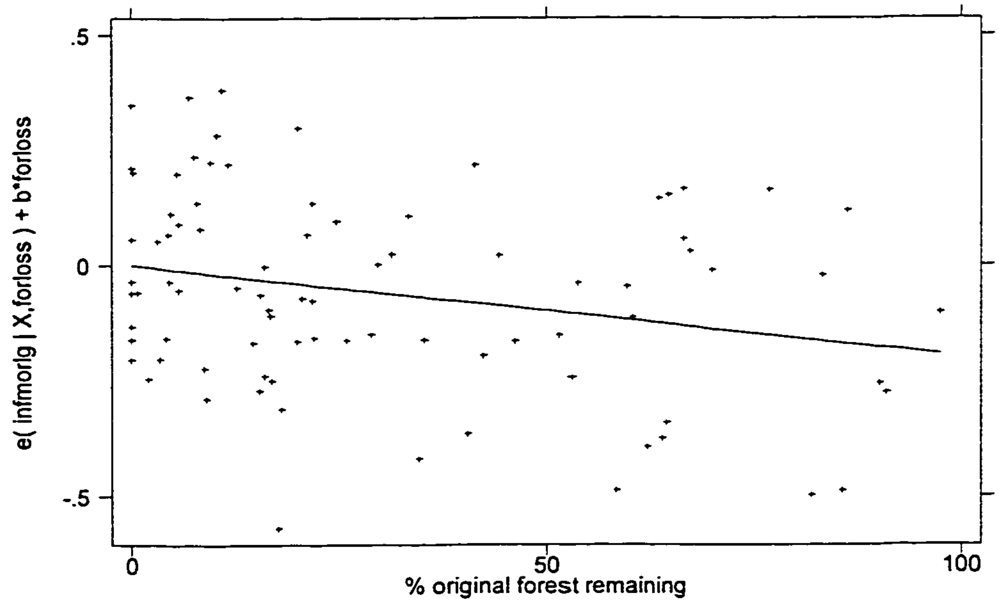

Figure 4.10.3 Component-plus-residual plot of forest remaining in log infant mortality model.

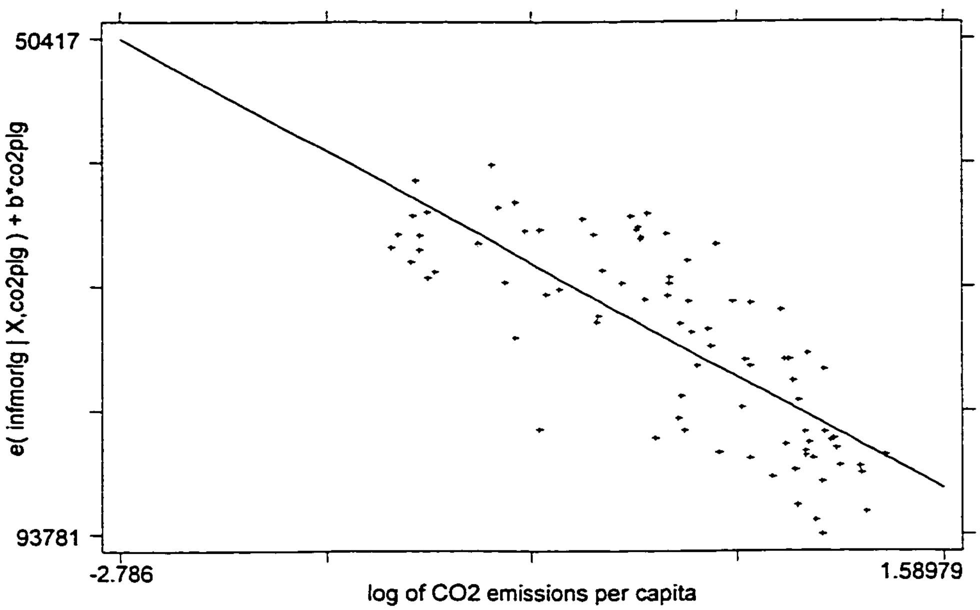

Figure 4.10.4 Component-plus-residual plot of log CO_2 emissions per capita in log infant mortality model.

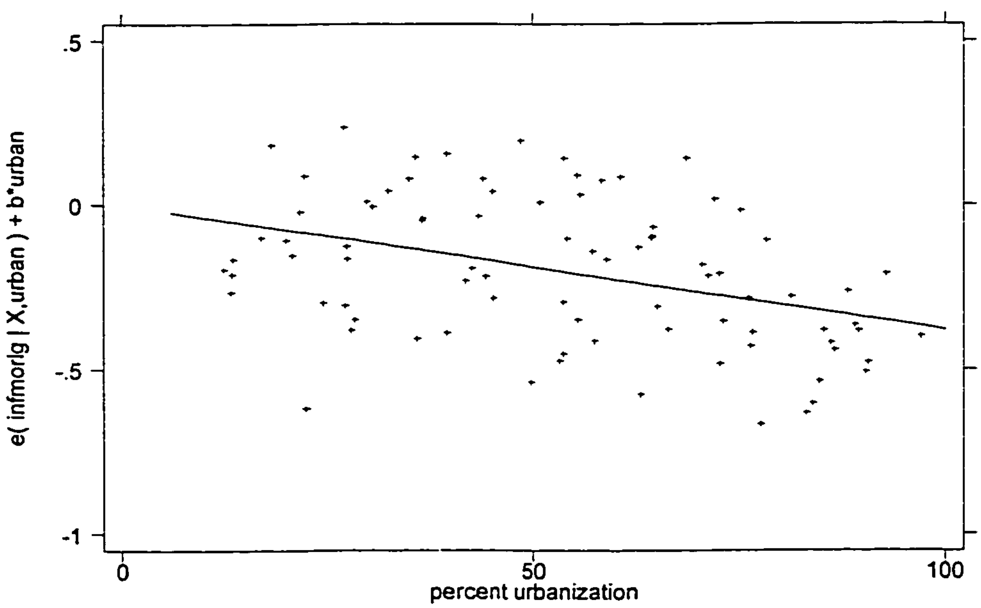

Figure 4.10.5 Component-plus-residual plot of urbanization in log infant mortality model.

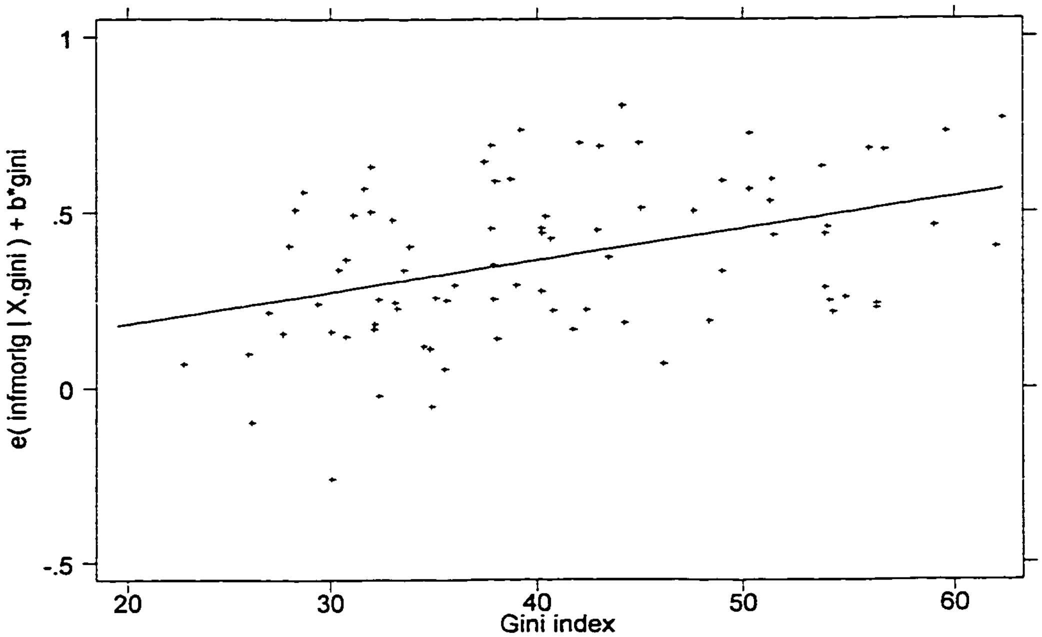

Figure 4.10.6 Component-plus-residual plot of Gini Index in log infant mortality model.

Here, our component-plus-residual plots indicate that perhaps log CO_2 emissions per capita could benefit from the addition of a quadratic term. In fact, when each is added to our main effects model (from Table 4.10.1), we find that the quadratic term for log CO_2 emissions per capita is significant and useful in the model. We also find that urbanization becomes non-significant in the model ($p = 0.060$), though not extremely so. In the end, we decided to keep urbanization in the model because it had the effect of changing the coefficient of log CO_2 emissions per capita by 18% when it was removed from the model. With the addition of a quadratic term (c2) for log CO_2 emissions per capita, the new model is summarized in Table 4.10.4.

Table 4.10.3 Revised main effects model with log infant mortality as outcome.

No. of obs = 85	R^2 = 0.8401					
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
high disturbance	-0.003	0.001	0.001	-0.004	-0.001	-0.185
forest remaining	-0.002	0.001	0.021	-0.004	0.000	-0.123
CO2 emissions per cap. (log)	-0.396	0.054	0.000	-0.503	-0.289	-0.636
urbanization	-0.003	0.002	0.061	-0.006	0.000	-0.148
Gini index	0.006	0.002	0.014	0.001	0.011	0.131
c2	-0.183	0.043	0.000	-0.267	-0.098	-0.207
constant	1.739	0.135	0.000	1.470	2.008	

Figure 4.10.7 provides the residual-versus-fitted plot for this revised model and shows no evidence of model misspecification.

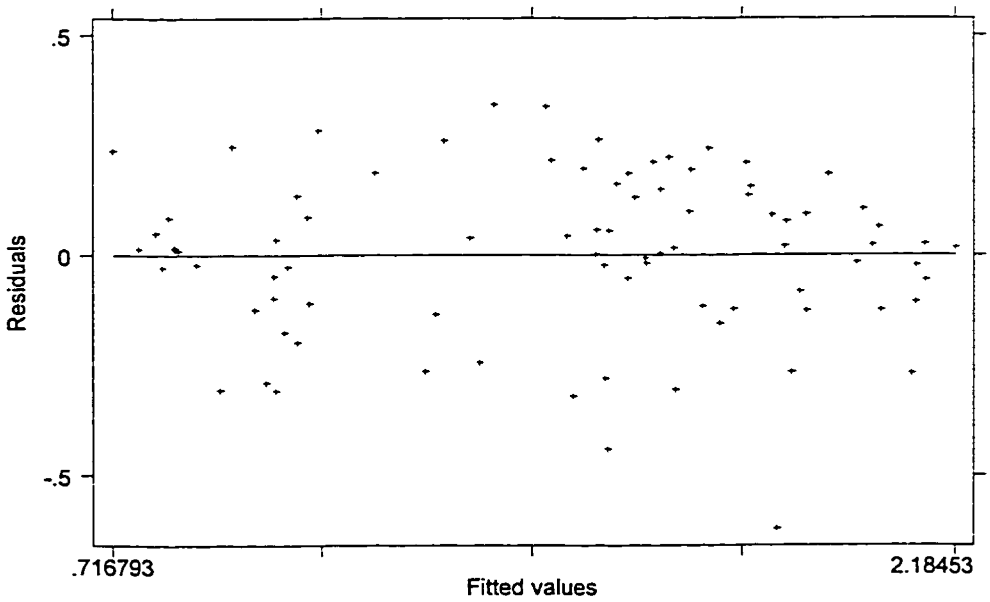

Figure 4.10.7 Residual-versus-fitted plot for revised main effects model predicting log infant mortality.

A further assumption of linear regression that we wish to test is that of constant variance. The values of the Cook-Weisberg test for heteroscedasticity are shown in Table 4.10.4.

We reject the null hypothesis of constant variance if the p-value of the test is less than 0.05. This table indicates that there are no significant problems with heteroscedasticity.

Table 4.10.4 P-values of the Cook-Weisberg test for heteroscedasticity – log infant mortality as outcome (Ho: constant variance)

Variable	p-value
high disturbance	0.784
forest remaining	0.500
CO2 emissions per cap. (log)	0.597
urbanization	0.635
Gini index	0.937

As in the previous analysis with life expectancy as the outcome, we used the above covariates to fit a model for each category of GDP per capita. As before, the medium chosen to visualize the model is a series of added-variable plots. Unlike the model for life expectancy, however, we have a quadratic term in the infant mortality model that is not easily displayed. Currently, there is no way of incorporating a quadratic term into an added-variable plot, nor is there a convenient tabular method to summarize a quadratic variable as a single term. To compensate, we have created added-variable plots for all variables *except* log CO_2 emissions per capita using the revised model with the quadratic term. This ensures that each of these variables is adequately adjusted for the quadratic nature of log CO_2 emissions per capita. However, for log CO_2 emissions per capita, we have estimated the model and created an added-variable plot without the quadratic term. We are confident that this will not unduly misrepresent our findings because an examination of the component-plus-residual plot for log CO_2 emissions per capita (Figure 4.10.4) indicates that, while the functional form is quadratic, it is not radically so.

Figures 4.10.8 through 4.10.12 show added-variable plots for each model covariate stratified across categories of GDP per capita.

Figure 4.10.8 depicts three added-variable plots (one for each category of GDP per capita) of the association between high disturbance and log infant mortality adjusted for the other independent variables in the model. It shows that the association is relatively weak, and consistently negative, for all levels of GDP per capita. This is consistent with the life expectancy model. There are some outliers in the low- and middle-income countries, but none appear to be particularly influential on the slope of the regression line. Among the high-income countries, Israel appears quite influential and Japan does not, despite that it is an outlier. However, removing only Israel makes Japan quite influential. Removing both only changes the slope coefficient from –0.002 to –0.001, which shows that Israel and Japan approximately balance one another and the original slope coefficient is not unduly influenced by outliers.

Figure 4.10.9 depicts three added-variable plots (one for each category of GDP per capita) of the association between percent original forest and log infant mortality adjusted for the other independent variables in the model. It shows that the association is relatively weakly negative among low- and medium-income countries, and quite significant among high-income countries. The most interesting outliers are in the high GDP per capita category with Israel, Sweden, and Japan appearing to have significant influence on the slope of the regression line. The removal of these countries actually results in the association changing from negative to weakly positive. The bulk of the data for high-income countries actually show very little association between original forest and log infant mortality.

Figure 4.10.10 depicts three added-variable plots (one for each category of GDP per capita) of the association between log CO_2 emissions per capita and log infant mortality adjusted for the other independent variables in the model. It shows that the association is relatively weakly negative among low-income countries, strongly negative among medium-income countries, and relatively weakly positive among high-income countries. There are no unduly influential outliers among the low- and middle-income countries. Among the high-income countries, the removal of the United States and Sweden reduces the slope coefficient further from 0.203 to 0.077, indicating that these two countries are quite influential on the original slope coefficient.

Figure 4.10.11 depicts three added-variable plots (one for each category of GDP per capita) of the association between urbanization and log infant mortality adjusted for the other independent variables in the model. It shows that the association is essentially non-existent among low-income countries, relatively weakly negative among medium-income countries, and weakly negative among high-income countries. Among the low-income countries, Nicaragua is an outlier, but it is in line with the bulk of the data. Among the middle- and high-income countries, there are quite a number of outliers; however, they seem to approximately balance one another out.

Figure 4.10.12 depicts three added-variable plots (one for each category of GDP per capita) of the association between the Gini index and log infant mortality adjusted for the other independent variables in the model. It shows that, despite the fact that it was significant in the overall model, the association is essentially non-existent when the results are stratified by GDP per capita. The outliers either are in line with the bulk of the data or approximately balance one another.

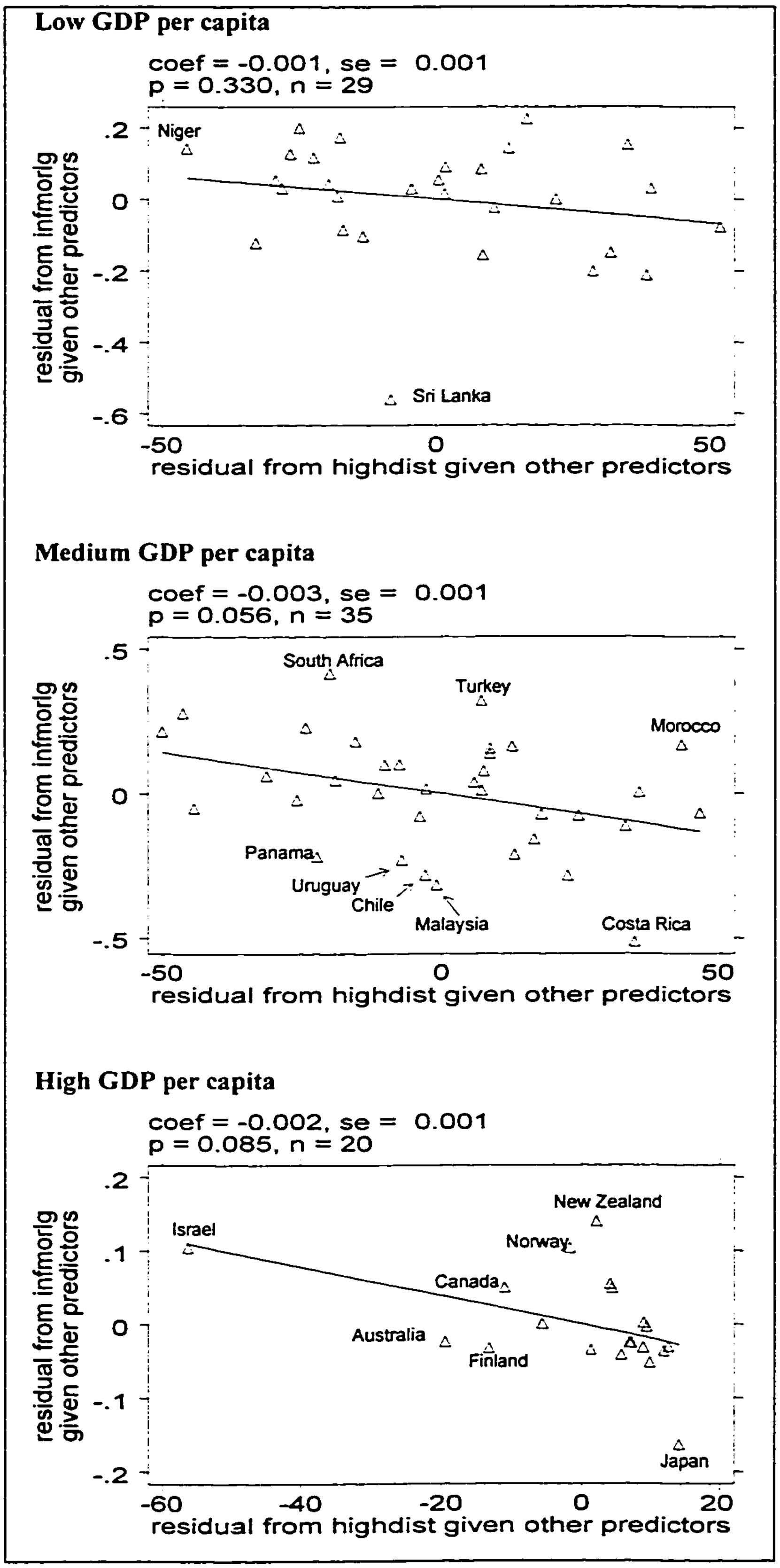

Figure 4.10.8 The association between high disturbance and log infant mortality adjusted for model covariates and stratified by GDP per capita category.

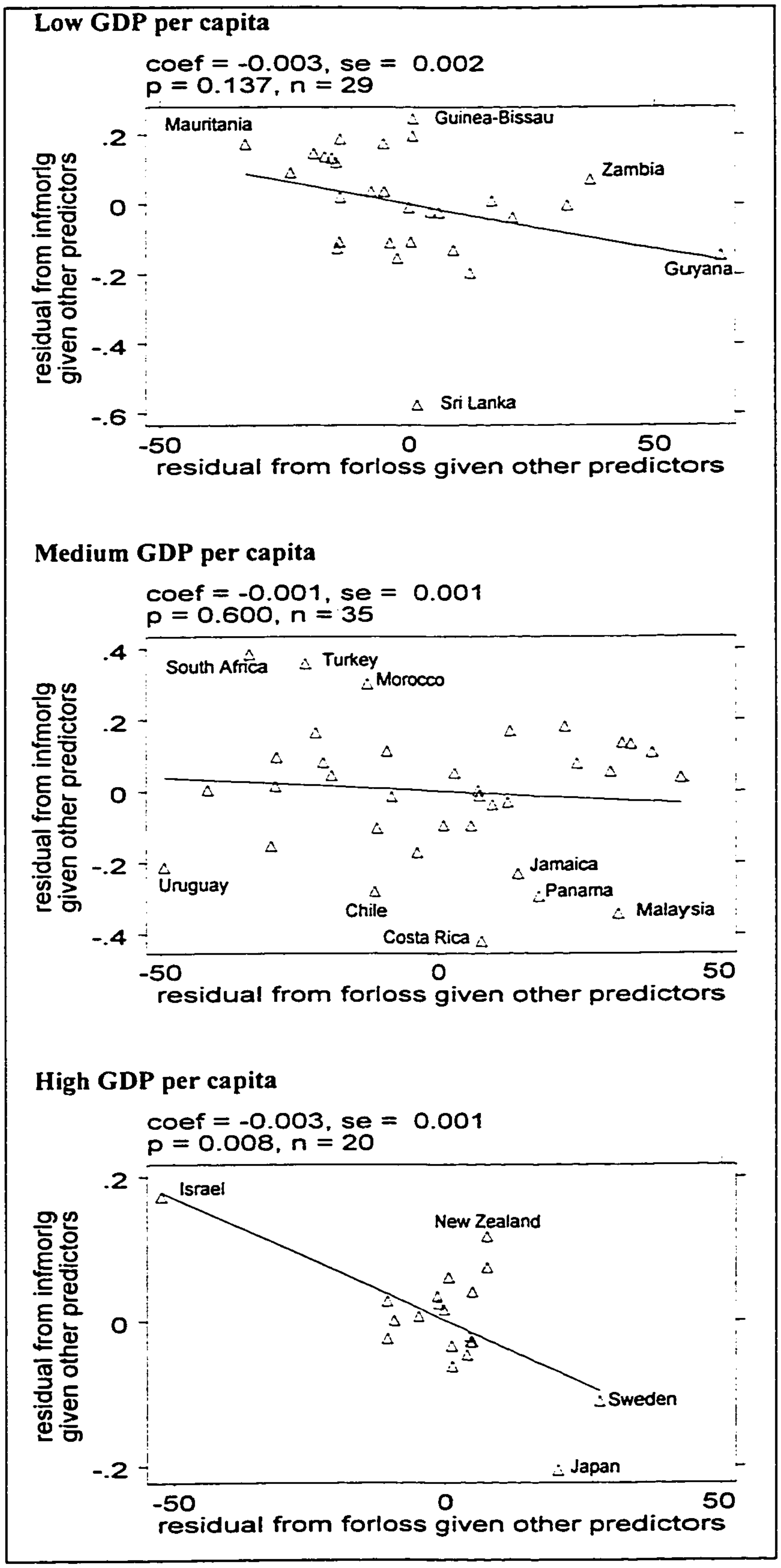

Figure 4.10.9 The association between % of original forest and log infant mortality adjusted for model covariates and stratified by GDP per capita category.

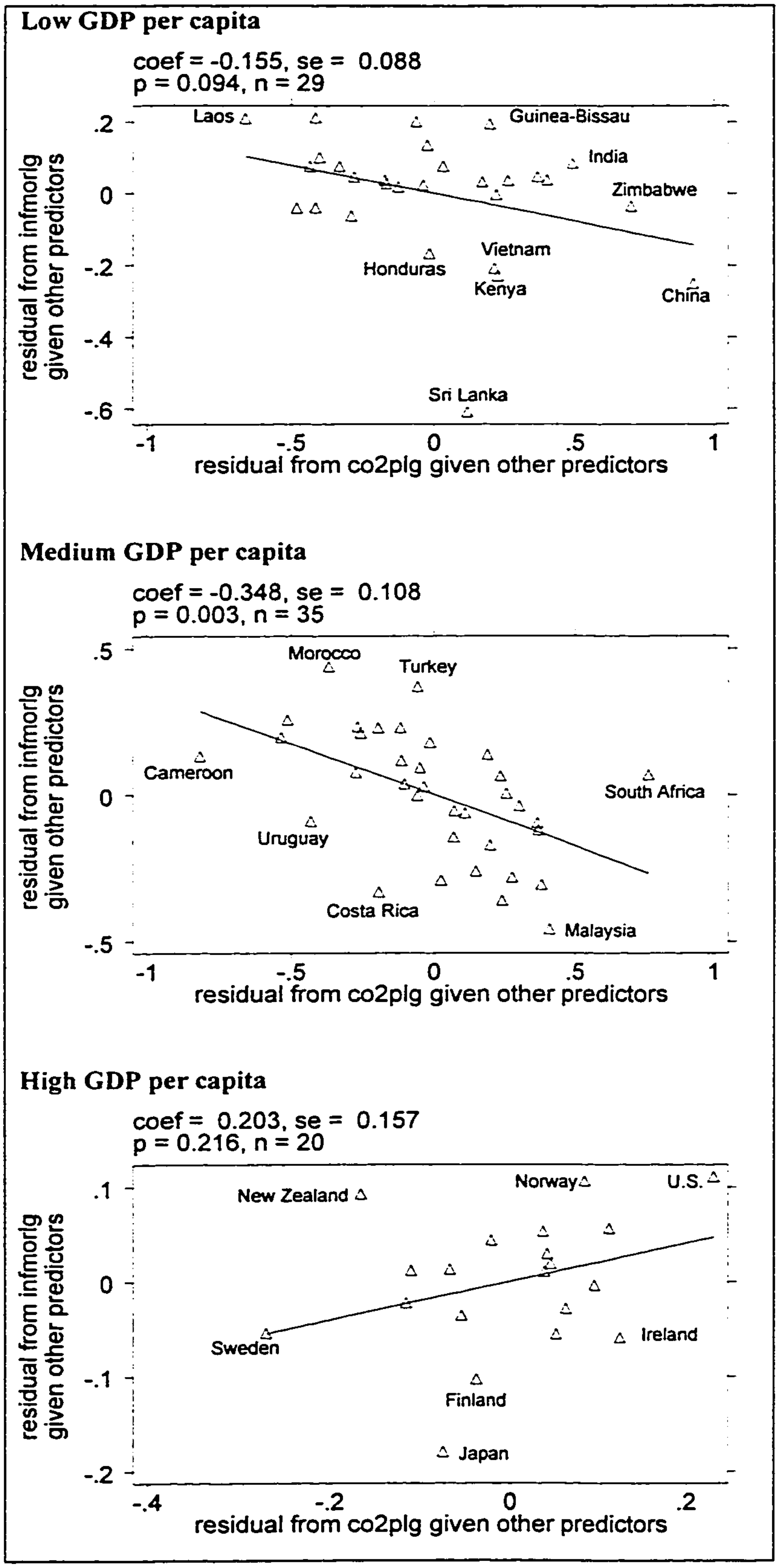

Figure 4.10.10 The association between log CO_2 emissions per capita and log infant mortality adjusted for model covariates and stratified by GDP per capita category.

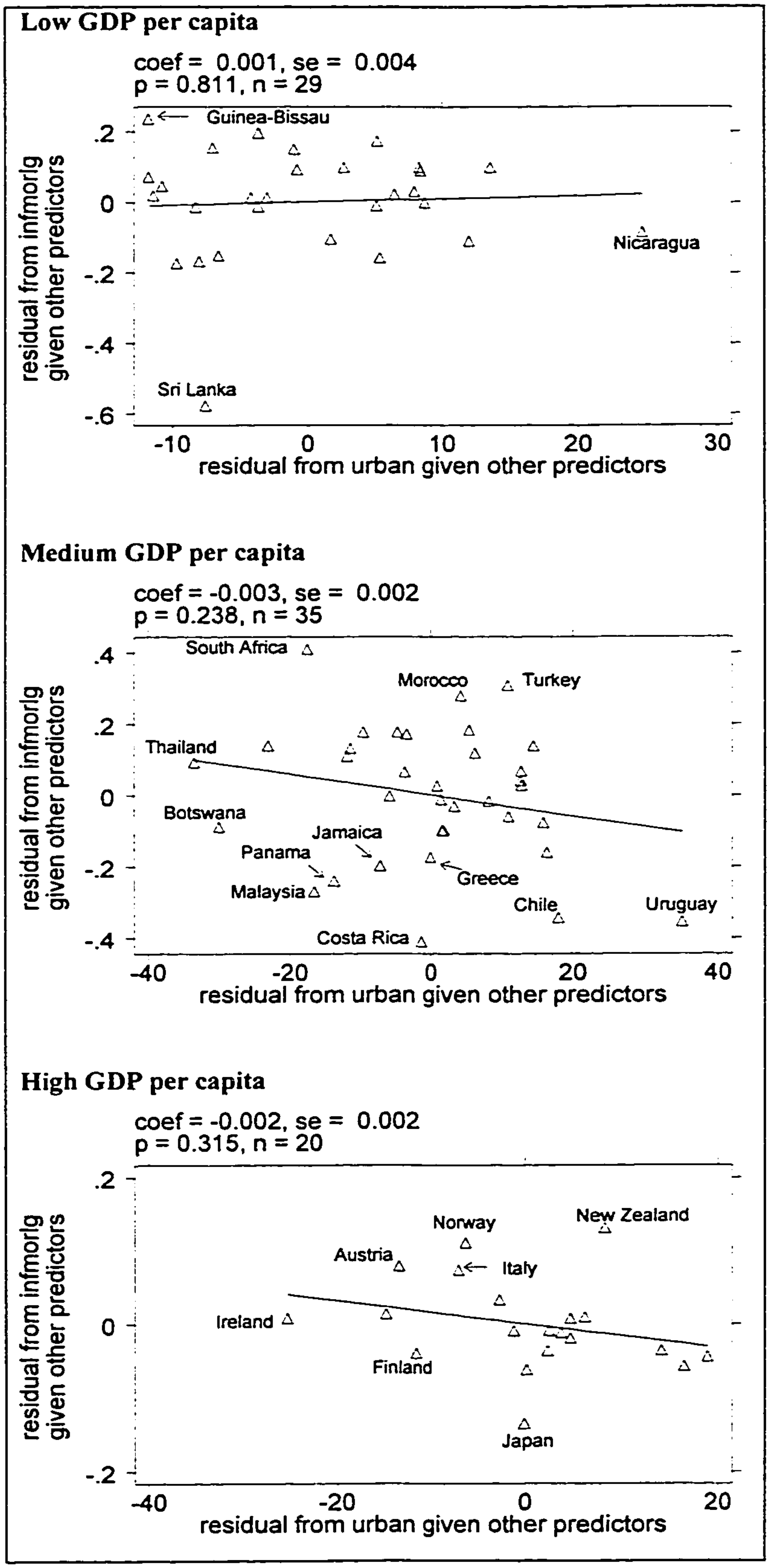

Figure 4.10.11 The association between urbanization and log infant mortality adjusted for model covariates and stratified by GDP per capita category.

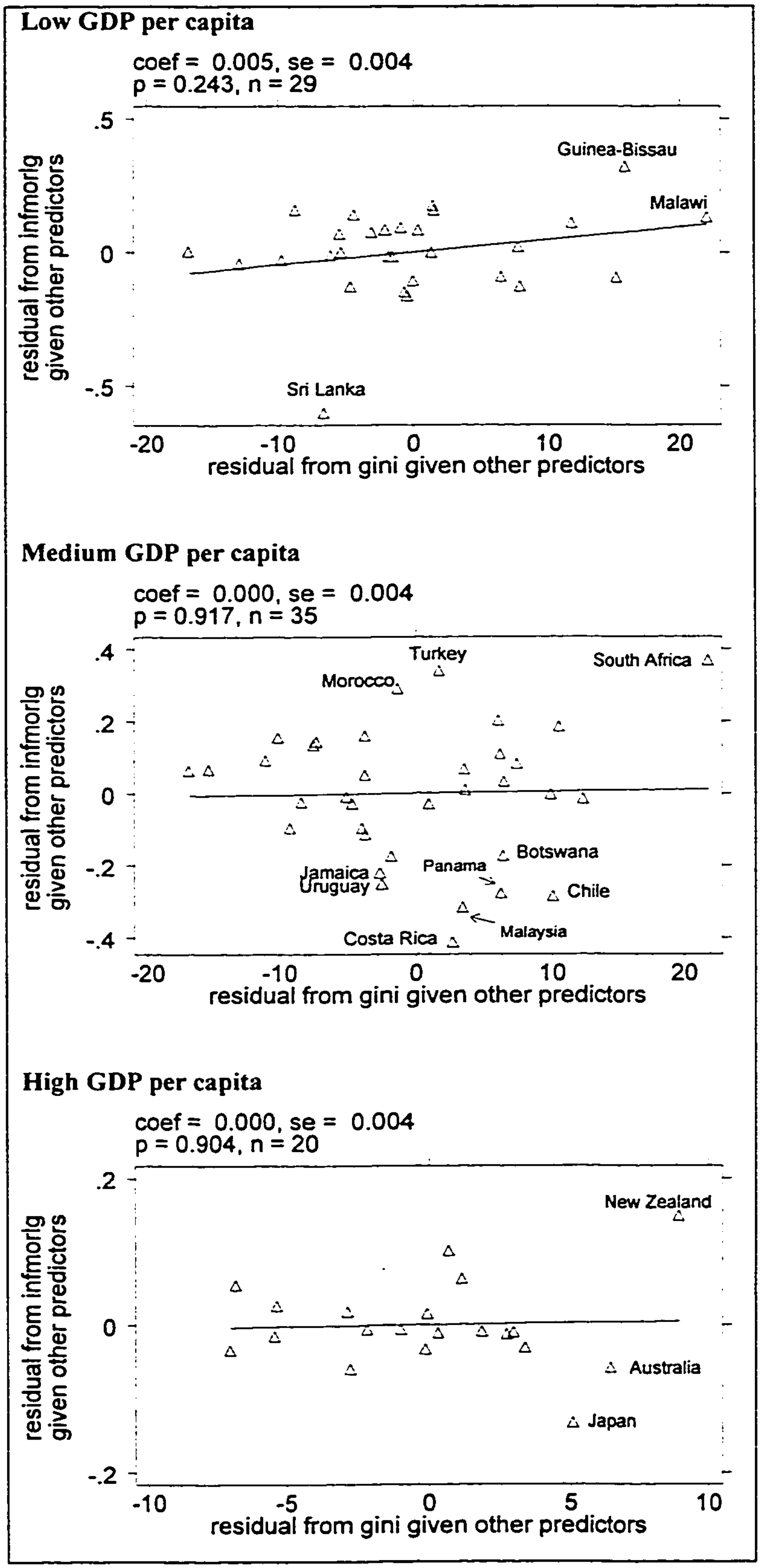

Figure 4.10.12 The association between the Gini index and log infant mortality adjusted for model covariates and stratified by GDP per capita category.

4.11 Multivariate Analysis – Low Birth Weight as Outcome

As with infant mortality, the univariate distribution of low birth weight was strongly skewed to the right. Therefore, we elected to use the $\log_{10}$ of low birth weight as our transformed outcome variable.

For the multivariate model with low birth weight as the outcome, we chose a model somewhat like those developed for the other two outcomes. In this model, we chose the four variables common to the other two models (high disturbance, original forest remaining, log CO_2 emissions per capita, and urbanization), as well as log population density and adult male literacy.

Table 4.11.1 provides the coefficients and characteristics of the initial multivariate main effects model predicting low birth weight.

Table 4.11.1 Main effects model with log low birth weight as outcome.

No. of obs = 94	R^2 = 0.6563					
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
high disturbance	-0.002	0.001	0.004	-0.003	-0.001	-0.285
deforestation	-0.029	0.012	0.017	-0.053	-0.005	-0.156
CO2 emissions per cap. (log)	-0.086	0.030	0.006	-0.146	-0.026	-0.321
urbanization	-0.002	0.001	0.013	-0.004	0.000	-0.258
population density (log)	0.128	0.035	0.000	0.058	0.197	0.343
adult male literacy	-0.002	0.001	0.012	-0.004	-0.001	-0.230
constant	1.192	0.091	0.000	1.011	1.373	

The model has a reasonable R^2 value of 0.6563, indicating that the predictors in the model explain about 66% of the variance in log low birth weight. Unlike the life expectancy and log infant mortality models, there was no one variable that was especially strong. The strongest predictors were log population density (R = 0.343) and log CO_2 emissions per capita (R = -0.321); the non-EI covariates generally were stronger than the indicators of EI.

We checked for the presence of collinearity by calculating variance inflation factors (VIFs). They are presented in Table 4.11.2 and indicate no serious collinearity.

Table 4.11.2 Variance inflation factors of model covariates (log low birth weight as outcome).

Variable	VIF
CO2 emissions per cap. (log)	3.71
urbanization	2.95
high disturbance	2.44
population density (log)	2.35
adult male literacy	2.19
deforestation	1.04
Mean VIF	2.45

Figure 4.11.1 is the residual-versus-fitted plot for this model. It shows an approximately random scattering of points indicating that we probably have not omitted any important variables.

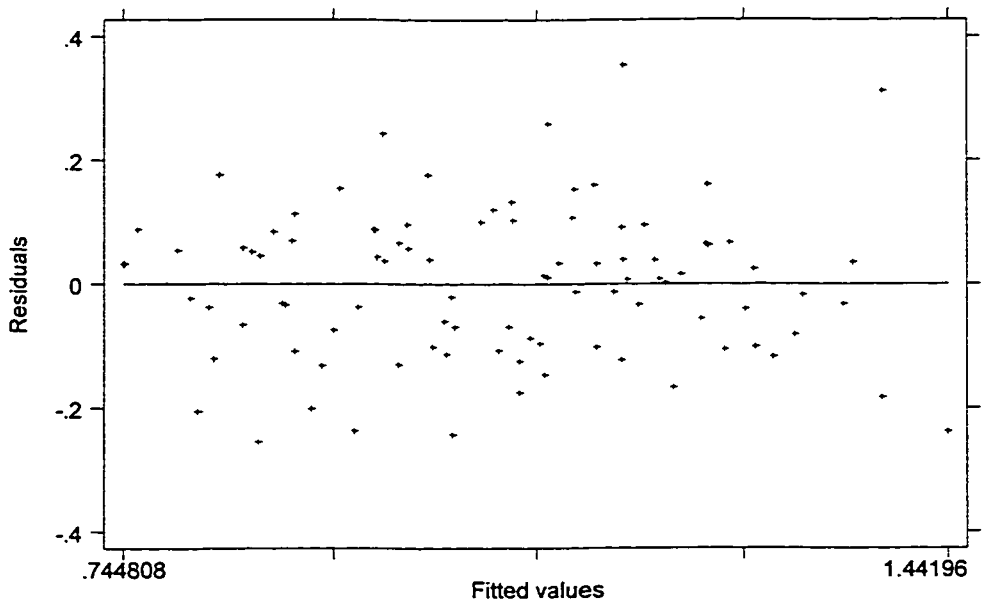

Figure 4.11.1 Residual-versus-fitted plot for main effects model predicting log low birth weight.

In order to check for the correct functional form of each of our covariates, Figures 4.11.2 through 4.11.7 display the component-plus-residual plot for each model covariate. In these plots, we are checking to see that each plot suggests an approximately linear fit.

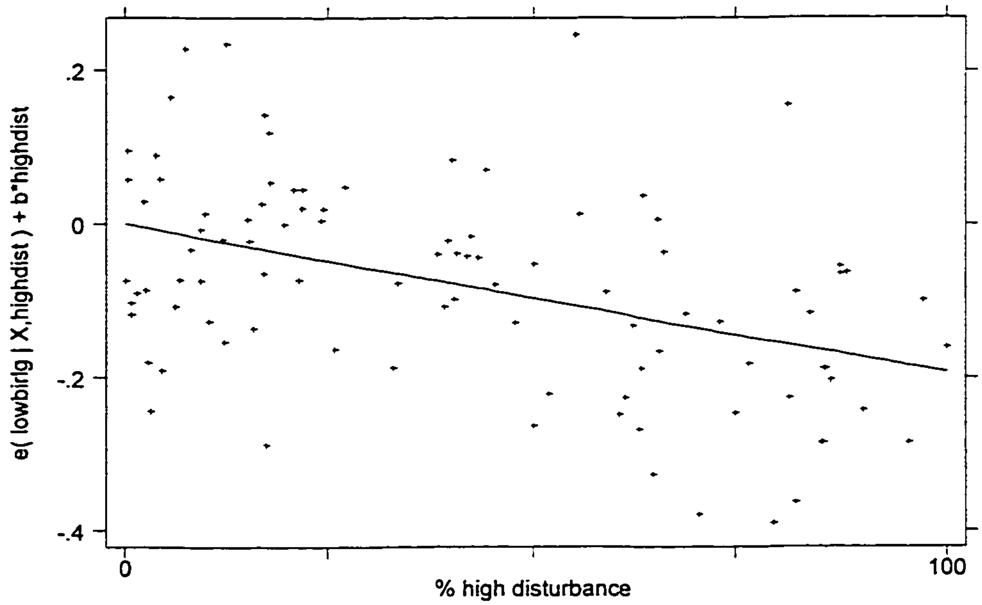

Figure 4.11.2 Component-plus-residual plot of high disturbance in log low birth weight model.

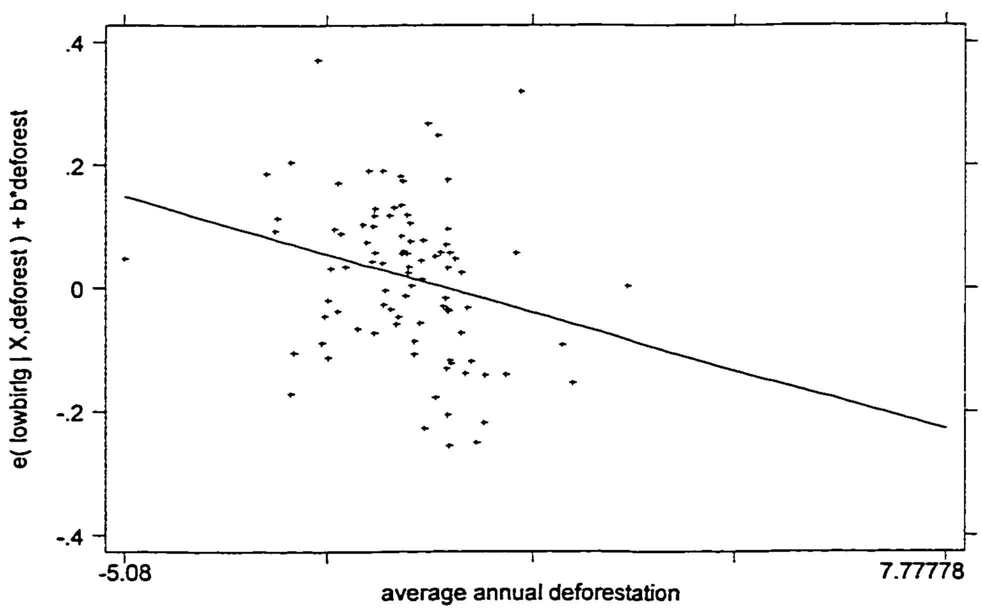

Figure 4.11.3 Component-plus-residual plot of annual forest change in log low birth weight model.

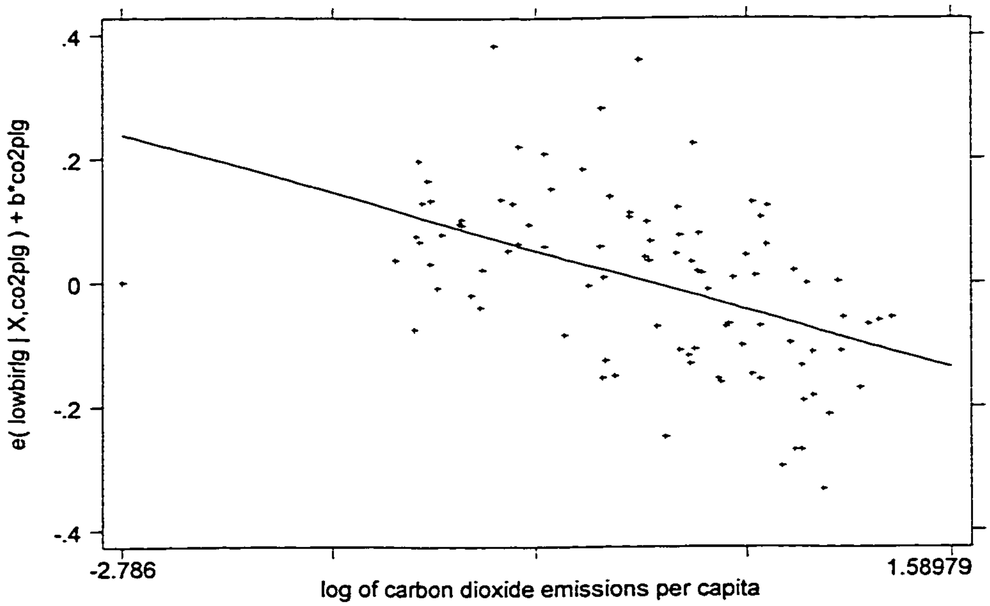

Figure 4.11.4 Component-plus-residual plot of log CO_2 emissions per capita in log low birth weight model.

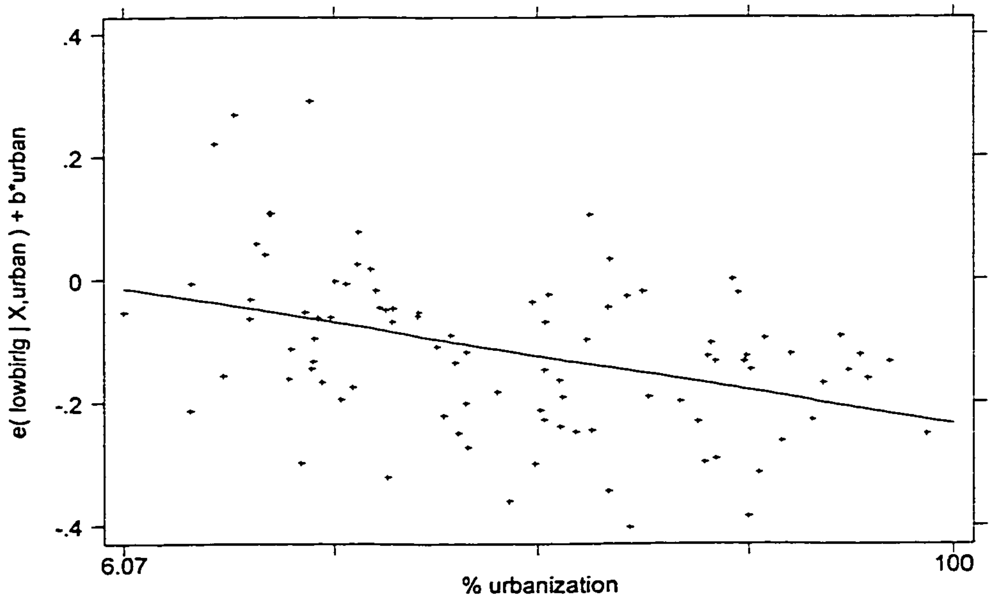

Figure 4.11.5 Component-plus-residual plot of urbanization in log low birth weight model.

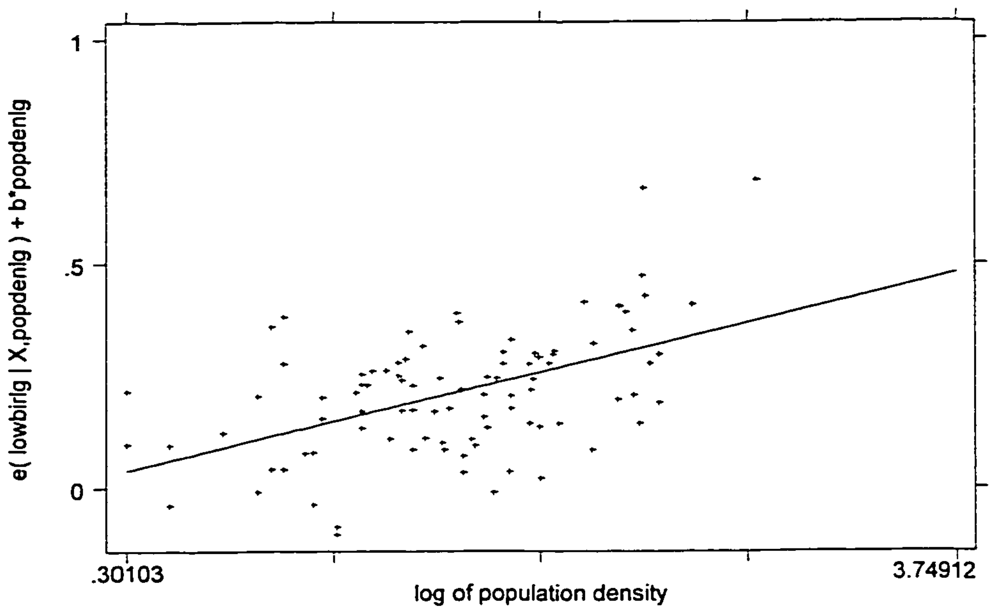

Figure 4.11.6 Component-plus-residual plot of log population density in log low birth weight model.

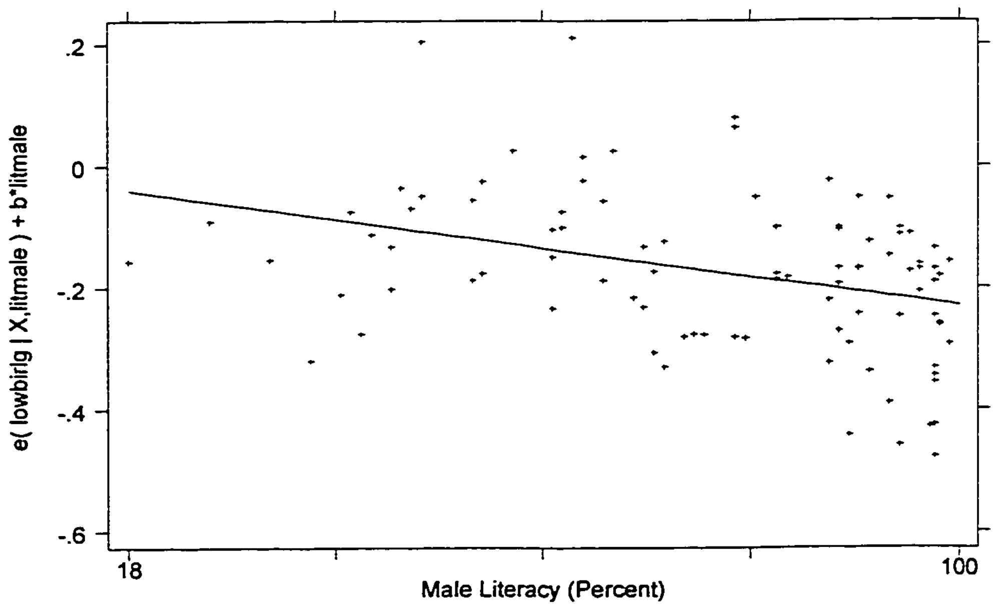

Figure 4.11.7 Component-plus-residual plot of adult male literacy in log low birth weight model.

Figure 4.11.6 and 4.11.7 indicate that the addition of quadratic terms for log population density and adult male literacy might improve the fit of the model. The quadratic term for log population density had some effect on the other coefficients when added to the model. However, when the two upper outliers in Figure 4.11.6 are removed, the quadratic term for log population density became much weaker. This instability led us to leave the quadratic term for log population density out of the model. The quadratic term for adult male literacy (*l2*), however, had an effect on the other model coefficients and added about 3% explained variance to the model; so, it was included in the model. Its association with log low birth weight did not appear to be especially influenced by outliers (Figure 4.11.7). Table 4.11.3 provides the revised model coefficients and characteristics.

Table 4.11.3 Revised main effects model with log low birth weight as outcome.

No. of obs = 94			R^2 = 0.6809			
	Coef.	Std. Err.	p-value	95% Conf. Interv.		R
high disturbance	-0.002	0.001	0.008	-0.003	0.000	-0.253
deforestation	-0.025	0.012	0.035	-0.049	-0.002	-0.134
CO2 emissions per cap. (log)	-0.087	0.029	0.004	-0.146	-0.029	-0.327
urbanization	-0.002	0.001	0.038	-0.004	0.000	-0.212
population density (log)	0.125	0.034	0.000	0.057	0.192	0.335
adult male literacy	0.008	0.004	0.051	0.000	0.017	0.841
l2	0.000	0.000	0.012	0.000	0.000	-1.116
constant	0.858	0.157	0.000	0.546	1.170	

The values of the Cook-Weisberg test for heteroscedasticity are shown in Table 4.11.4. We reject the null hypothesis of constant variance if the p-value of the test is less than 0.05. This table indicates that we have no significant problems with heteroscedasticity.

Table 4.11.4 P-values of the Cook-Weisberg test for heteroscedasticity – log low birth weight outcome (Ho: constant variance)

Variable	p-value
high disturbance	0.383
deforestation	0.836
CO2 emissions per cap. (log)	0.937
urbanization	0.117
population density (log)	0.091
adult male literacy	0.895
l2	0.7713

Like the model we developed for log infant mortality as the outcome, the model we currently are estimating has a quadratic term. Hence, we have again provided added-variable plots duly adjusted for the quadratic term for all variables except that of adult male literacy. The added-variable plots for adult male literacy are constructed from the model estimated without the quadratic term.

In the two previous models (namely, life expectancy and log infant mortality as outcomes), we stratified our added-variable plots across low, medium, and high categories of GDP per capita. We found that when we stratified this model by three categories of GDP per capita, we had so few countries in the highest category that we could not estimate a model. Therefore, for this model we have stratified across two levels of GDP per capita, the separation point being the median. Therefore, Figures 4.11.8 through 4.11.13 show the added-variable plots for each model covariate stratified across two categories of GDP per capita.

Figure 4.11.8 depicts two added-variable plots (one for each category of GDP per capita) of the association between high disturbance and log low birth weight adjusted for the other independent variables in the model. It shows that the association is consistently negative across both levels of GDP per capita. There are several outliers, but no particularly influential points.

Figure 4.11.9 depicts two added-variable plots (one for each category of GDP per capita) of the association between percent original forest and log low birth weight adjusted for the other independent variables in the model. It shows that the association is relatively strong and negative for both low- and high-income countries. The most interesting outliers in the low GDP per capita category are Pakistan, Paraguay, India, Jordan, Rwanda, and Egypt. The removal of these countries increases the slope coefficient from –0.044 to –0.091. In the high GDP per capita category, a similar phenomenon occurs after the removal of Jamaica, Thailand, Costa Rica, Portugal, and Tunisia. The slope coefficient changes from –0.049 to –0.092.

Figure 4.11.10 depicts two added-variable plots (one for each category of GDP per capita) of the association between log CO_2 emissions per capita and log low birth weight adjusted for the other independent variables in the model. It shows that the association is very weakly negative among low-income countries, and moderately negative among high-income countries. There are no unduly influential outliers.

Figure 4.11.11 depicts two added-variable plots (one for each category of GDP per capita) of the association between urbanization and log low birth weight adjusted for the other independent variables in the model. It shows a moderate negative association among the low-income countries and a moderate positive association among the high-income countries. There are no especially influential outliers among either the low- or the high-income countries.

Figure 4.11.12 depicts two added-variable plots (one for each category of GDP per capita) of the association between log population density and log low birth weight adjusted for the other independent variables in the model. It shows a moderate positive association between log population density and log low birth weight across both categories of GDP per capita. No outliers appear to be unduly influential on the regression slope.

Figure 4.11.13 depicts two added-variable plots (one for each category of GDP per capita) of the association between log population density and adult male literacy adjusted for the other independent variables in the model. It shows a moderate negative association between adult male literacy and log low birth weight across both categories of GDP per capita. Among the low-income countries, no outliers appear to be unduly influential on the regression slope. However, among the high-income countries, the removal of Algeria, Tunisia, Jamaica, and Thailand changes the slope coefficient from –0.003 to –0.014, making the relationship strongly negative.

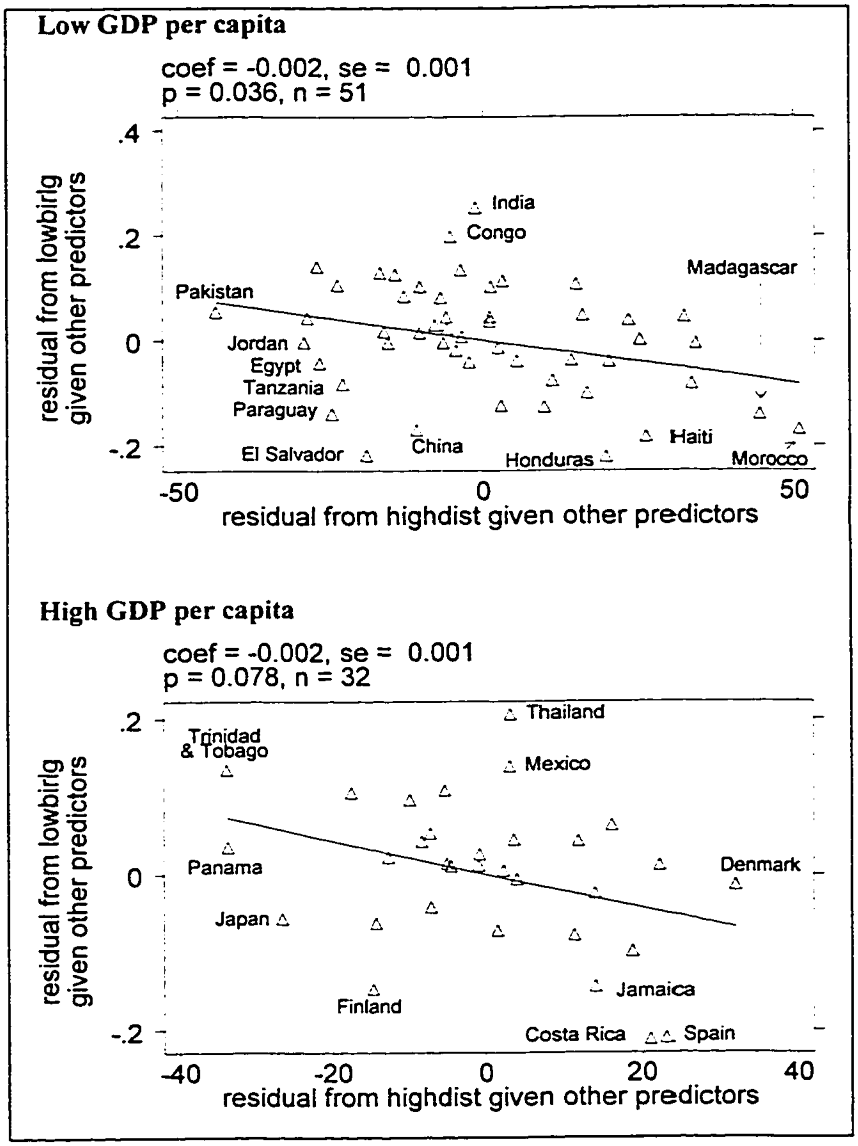

Figure 4.11.8 The association between high disturbance and log low birth weight adjusted for model covariates and stratified by GDP per capita category.

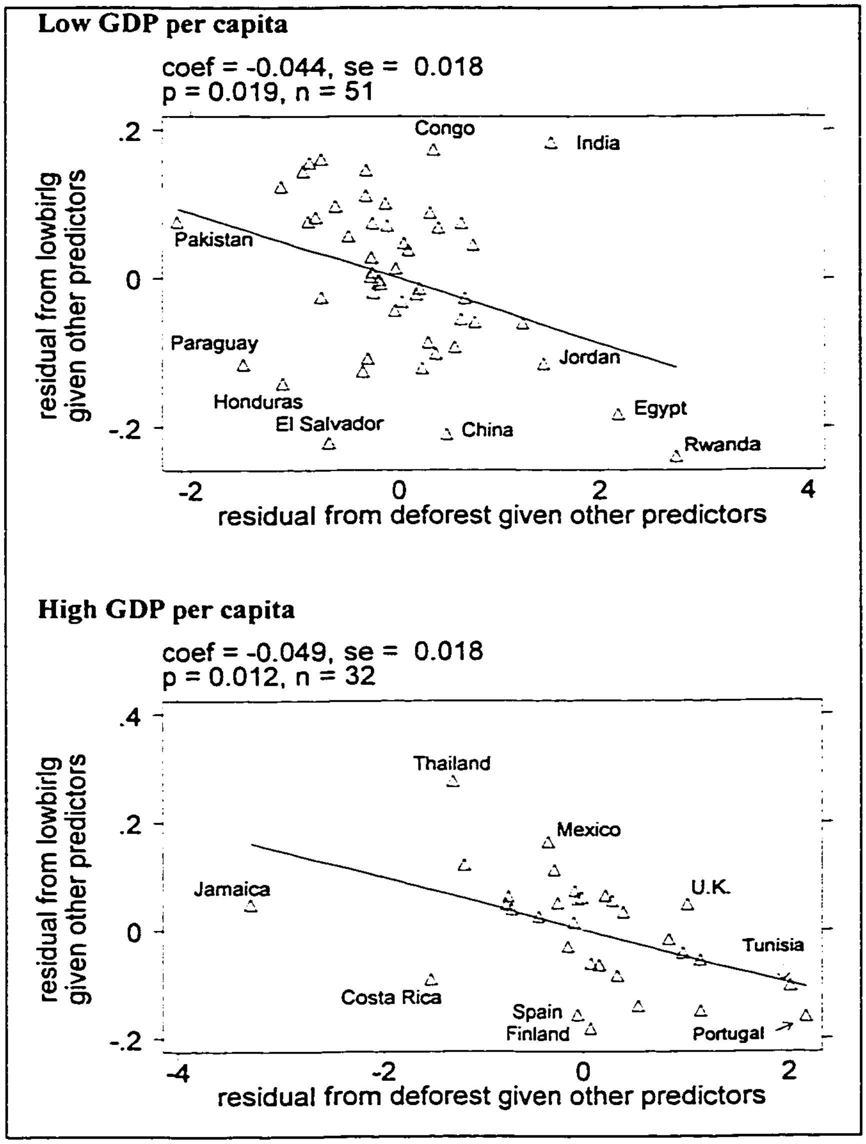

Figure 4.11.9 **The association between average annual forest change and log low birth weight adjusted for model covariates and stratified by GDP per capita category.**

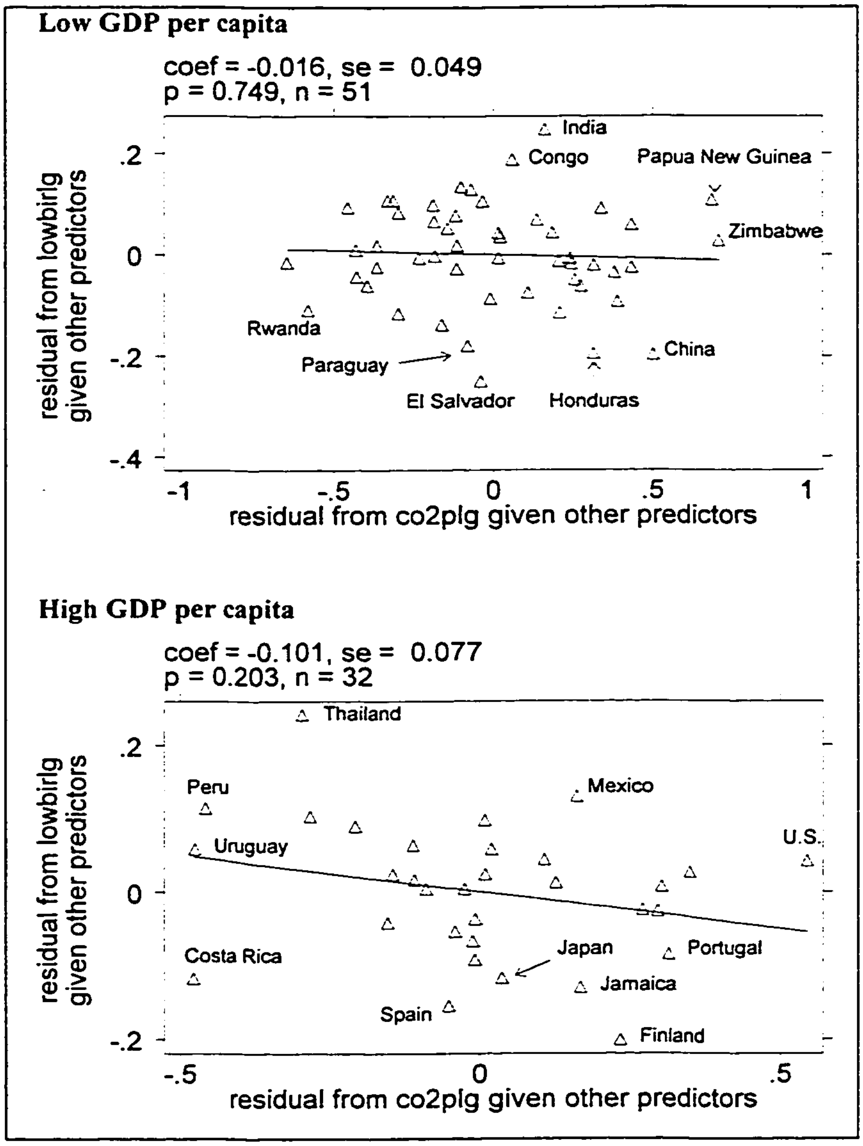

Figure 4.11.10 **The association between log CO_2 emissions per capita and log low birth weight adjusted for model covariates and stratified by GDP per capita category.**

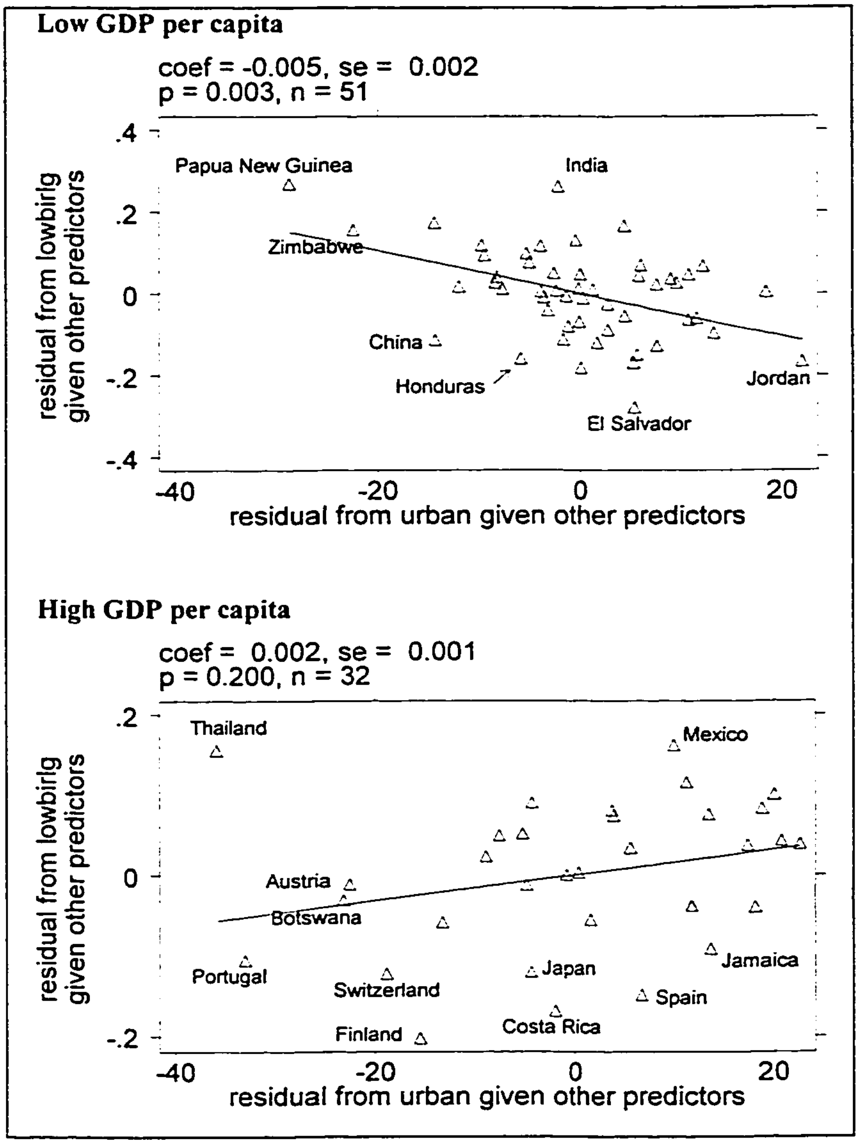

Figure 4.11.11 **The association between urbanization and log low birth weight adjusted for model covariates and stratified by GDP per capita category.**

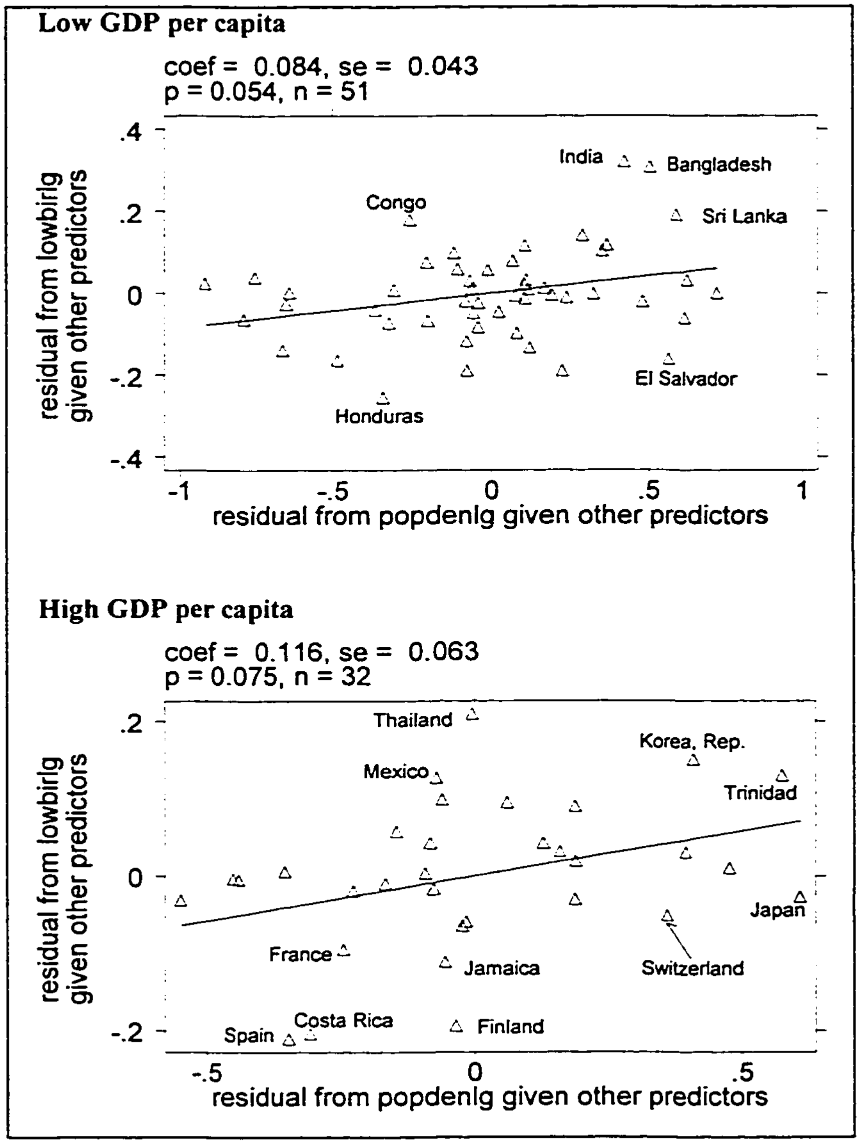

Figure 4.11.12 The association between log population density and log low low birth weight for model covariates and stratified by GDP per capita category.

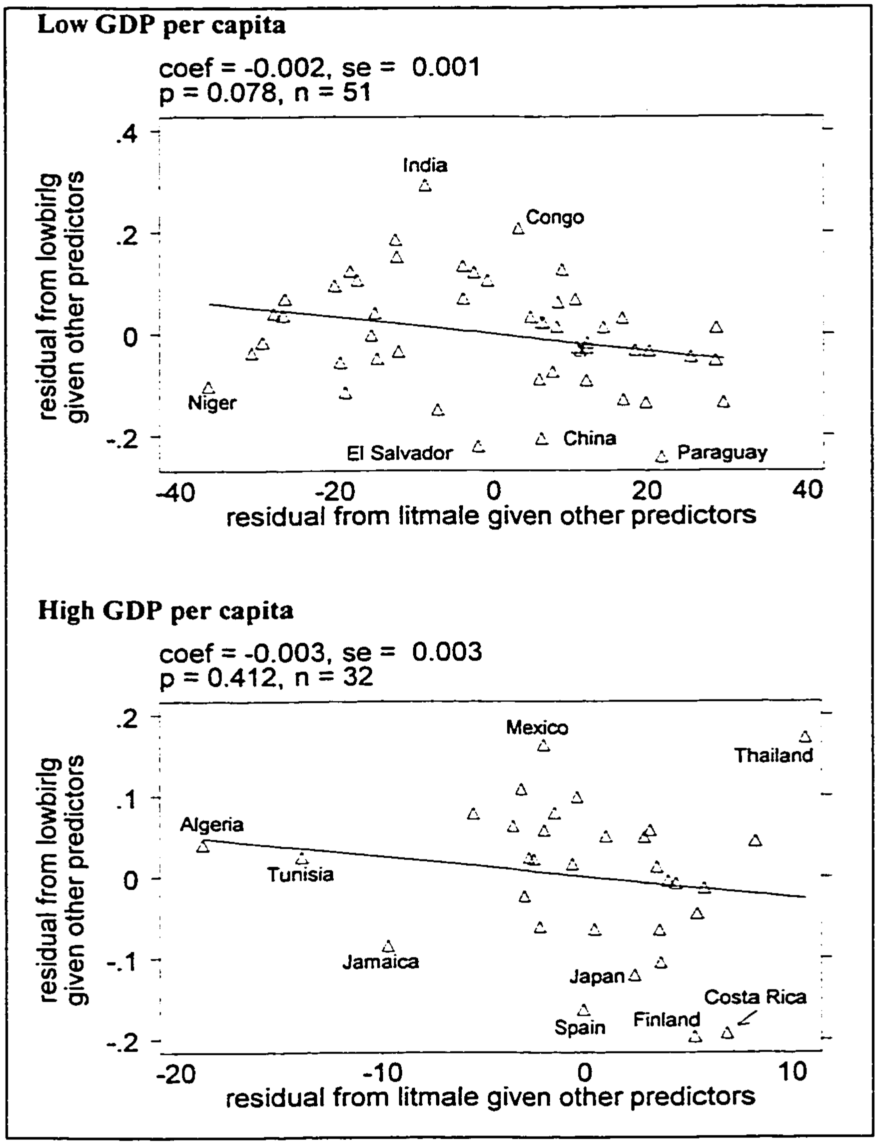

Figure 4.11.13 The association between adult male literacy and log low birth weight adjusted for model covariates and stratified by GDP per capita category.

Chapter 5 - Discussion

5.1 EI Variables

Despite the shortcomings of having to use population-based averages, the availability of only a single cross-sectional set of data, variable data quality, uncertain causal mechanisms, and the necessity of using surrogates of EI instead of direct measurements, a few associations between some of our EI variables and the three human health outcomes we considered were found. Most of these associations were in the expected direction from a development point of view, but perhaps in the opposite direction from an environmental perspective. That is, increasing development was associated with increasing health. The decrease in global EI associated with burgeoning development for the most part did not mitigate this association in this data set.

It is noteworthy that, regardless of which of our three outcomes were considered, it is always the same two EI variables that are important in the regression model. One of those variables, and in fact our most plausible measure of EI (or, rather, the lack of EI), is the percentage of land that is "highly disturbed" by human occupation. This high disturbance variable is most plausible because it represents the percentage of land that is entirely the opposite of the "wildness" criterion for EI. Our results suggest that the conversion of land to permanent human use has a small association with improving human health. This association was consistent for all three outcomes as well as across levels of GDP per capita. Nor does the association appear to be appreciably influenced by outliers. This should not be entirely surprising to people who live in well-built houses with central heating, built-in water and sewage lines, and electricity. Nor should it be surprising to those in developed countries who regularly go to supermarkets over-flowing with food grown on large, high-intensity farms all over the globe. Clearly, humans are not physically equipped to live in the "natural" world, nor does the natural world provide an optimal environment for human ends (such as growing large amounts of food). Instead, we build houses in cold places and, lacking a natural layer of fur or blubber, we must heat them with wood or fossil fuels. To feed our burgeoning numbers we turn vast areas of natural grassland into high-output farms. In short, we benefit immensely from, in fact our population is built on, the conversion of wilderness to super-efficient, controlled, human-centred environments. The question facing us is that of how far this trend of converting natural areas to human use can persist before these positive effects on human health become deleterious.

In addition, we must not forget that the relationship between high disturbance and human health – as measured in this study – has been adjusted for industrialization and urbanization. It also has been stratified across levels of GDP per capita, which, in turn, was adjusted for cost of living, and the relationship remained remarkably consistent. This suggests that the relationship between increasing high disturbance and improving indicators of population health is not entirely explainable by wealth, industrialization, or urbanization. Nor is it explainable by the other covariates that were examined, but found unimportant in the final model; namely, population density and educational level. Thus, the relationship between high disturbance and health likely represents something very subtle and, as yet, unexplained.

The second EI variable that was consistently important is the percent of original forest remaining or its close relative, average annual change in forest cover. Increasing values of original forest cover remaining and average annual change in forest cover appear to be generally associated with improving health status (Figures 4.9.8, 4.10.9, and 4.11.9). Unlike the relationship between the high disturbance and health, which is consistent with a pro-development perspective, this association between leaving forests intact and improving human health favours the EI hypothesis. This remained true even after adjusting for the positive association between increasing socio-economic development and improving health. Unlike the association between high disturbance and human health across levels of GDP per capita, sometimes the association between annual change in forest cover and human health was heavily influenced by outliers. In particular, Figure 4.10.8 shows that the relationship between percent original forest and log infant mortality for high GDP per capita countries would be reversed if the three outliers were deleted. The outlier in the extreme upper left corner (Israel) particularly influences the line to have a negative slope. In a forthcoming section, we discuss the utility of outliers and indicate that a detailed analysis of outliers is beyond the scope of this thesis. In point of fact, this particular outlier a reminder that an adequate analysis of the outliers necessitates a great deal of expertise in geography and politics. It is tempting to discount this outlier on the assumption that Israel is a largely desert country with almost no forest cover in the first place. A visitor to Israel informed us that this is a common, but quite untrue, assumption.

As interesting as those EI variables that were included in the model, are those that had no effect on the model. In this study, the conservation of biodiversity as measured by the percentage of species threatened, and land protection, as measured by the percentage of land recognized by the IUCN as fully or partially protected, appears to have no relationship to any of the three human health outcomes. This is noteworthy because biodiversity and land protection are cornerstones of the environmental movement. However, there has yet to be a convincing causal mechanism quantitatively demonstrated regarding either biodiversity or land protection and human health.

The usual claim for the protection of biodiversity involves the *potential* loss of as yet undiscovered therapeutic drugs in the tropical rain forest. The land protection argument has somewhat more credence in that it seems reasonable to protect sites with key benefits for humanity, such as watersheds and fish spawning grounds. However, it may be that it is not the key sites that are being protected. For instance, some have criticized Canada for protecting much rock and ice in the mountain parks, but very little else. In the case of the Grand Banks off the coast of Newfoundland, for instance, the very spawning grounds that should have been protected were the richest sources of commercial fish. Unfortunately, they were not protected. Perhaps, if the most important areas had been protected we might see a positive relationship between human health and land protection.

5.2 Confounders

There are two confounders that appear consistently in the models predicting all three of the health outcomes examined in this study. They are log CO_2 emissions per capita and urbanization. Log CO_2 emissions per capita is the strongest variable, other than GDP per capita, for predicting all of the human health outcomes examined in this study. In addition, it shows a fairly consistent relationship across the three different outcomes. For both life expectancy and log infant mortality, the relationship between these and log CO_2 emissions per capita is strongly positive among low and medium income countries (for life expectancy as outcome: $R = 0.667$ and $R = 0.392$ respectively; for log infant mortality as outcome: $R = -0.393$ and $R = -0.495$ respectively) and strongly negative for high income countries (for life expectancy as outcome: $R = -0.504$; for log infant mortality as outcome: $R = 0.319$). Thus, industrialization appears to be both a boon and a burden. In low and middle income countries, industrialization is necessary to improve our health measures. In high income countries, now that we have reaped the health benefits of economic growth and stability, the negative health consequences have become manifest (e.g., over-consumption and possibly pollution).

The second confounder that appears consistently in all of the models is urbanization. In the life expectancy and log infant mortality models, the association between these two health measures and urbanization seems to become stronger with increasing income. In low income countries, the association is negative, but quite weak (for life expectancy as outcome: $R = -0.114$; for infant mortality as outcome: $R = 0.024$). In middle and high income countries, however, the association is positive and considerably more pronounced (for life expectancy as outcome: $R = 0.257$ and $R = 0.447$ respectively; for infant mortality as outcome: $R = -0.188$ and $R = -0.456$ respectively). This suggests that in poor countries, the benefits of urbanization are overshadowed by negative effects, perhaps because sanitation measures in large cities in developing countries generally are poor and that crowding results in increased disease transmission. In middle and high income countries, where public health measures such as sanitation are generally strong, urbanization is associated with improvements in these two health outcomes.

For log low birth weight as the health outcome, where the results were stratified into only low and high income (owing to a dearth of data points), we see the opposite trend. In low income countries, the percentage of low birth weight babies decreases with increasing urbanization ($R = -0.450$). In contrast, in high income countries, the percentage of low birth weight babies increases with increasing urbanization ($R = 0.203$).

Why infant mortality and low birth weight, which are related variables ($R = 0.821$), should display opposite trends with regard to urbanization is perplexing. One reason may be that the models took into consideration different covariates. For instance, while log population density was not found to be important in the model for infant mortality, it was found to be important in the low birth weight model. However, that does not necessarily mean that within certain strata of GDP, log population density is not important. In this study, we modeled each outcome and then stratified the model by levels of GDP per capita. Perhaps an appropriate avenue for future research would be to model each GDP stratum of each outcome separately. This has the disadvantage that the modeler has fewer data points in each stratum on which to base a reliable model. However, as additional data are collected, perhaps some of the gaps in the current data set will be filled, making this approach more feasible.

In addition to log CO_2 emissions per capita and urbanization, which were important in all three models, the models using log infant mortality and log low birth weight included additional covariates. The presence or absence of the Gini Index was found to effect the other covariates in the log infant mortality model. Therefore, it was considered prudent to include it in the main effects model to account for its confounding effect on the other covariates. After stratification by GDP per capita, however, its association with the outcome was found to be important only among low income countries ($R = 0.220$; see Figure 4.10.12).

The model with log low birth weight as the outcome had the largest number of covariates. It included high disturbance, log CO_2 emissions per capita, and urbanization; and, instead of original forest remaining, we used the alternative forestry variable, namely, annual change in forest cover. In fact, we tried the model with both original forest remaining and with annual change in forest cover. We found that either original forest remaining or annual change in forest cover could be included, but that annual change in forest cover had a marginally greater association with the other covariates in the model. Once one of the covariates had been added, however, the addition of the other did not have much effect on the model.

In addition, the log low birth weight model included log population density and adult male literacy. The correlation between log population density and log low birth weight was positive for both high and low income populations. Thus, increasing population density is associated with an increasing percentage of low birth weight babies, regardless of income level.

The correlation between adult male literacy, a surrogate for education, and log low birth weight was negative for both high and low income countries (R = -0.240 and R = -0.287 respectively). This indicates that increasing literacy was associated with a decrease in the percentage of low birth weight babies, perhaps because better-informed parents make better maternal health decisions.

5.3 The Role of GDP per Capita

Early in the modeling, we discovered that GDP per capita would play an important role in this study. Every attempt at modeling that included GDP per capita, quickly eliminated all other covariates in the model. For example, consider Table 5.3.1 in which a comparison of correlation coefficients before and after the addition of GDP per capita is presented. We can see that all of the covariates in the model become quite insignificant in the presence of the overwhelming effect of GDP per capita. This indicates the presence of strong confounding.

Table 5.3.1 Comparison of life expectancy model with and without GDP per capita in the model.

	Multiple R	
	without GDP	with GDP
Forest Remaining	0.098	-0.012
High Disturbance	0.191	0.016
CO_2 emissions per capita	0.621	0.061
Urbanization	0.215	0.036
GDP per capita		0.819

This same effect was seen regardless of the outcomes and covariates that we chose. Always, GDP per capita would overwhelm the other variables in the model. Thus, we knew that GDP per capita was important, but we could not add it to the model. There are two issues, one practical and one theoretical.

First, as a matter of practicality, one way to control for a variable is to make categories and then stratify in the analysis by these categories. As mentioned earlier, we divided GDP per capita into three categories based on the World Bank categories of low, medium, and high income. Then, we applied our models within each of the three categories. This method of controlling for the confounding effect of GDP per capita is less effective than adding it to our regression model as a continuous covariate. The reason is that there is still a lot of variability *within* the categories of GDP. Ideally, one would have a situation similar to Figure 5.3.1, in which the within category slope would be zero (no relationship). Then, this method of controlling for confounding would work perfectly. On the other hand, from a descriptive point of view, it is useful to be able to discern those factors that vary in their associations across low, medium, and high income countries.

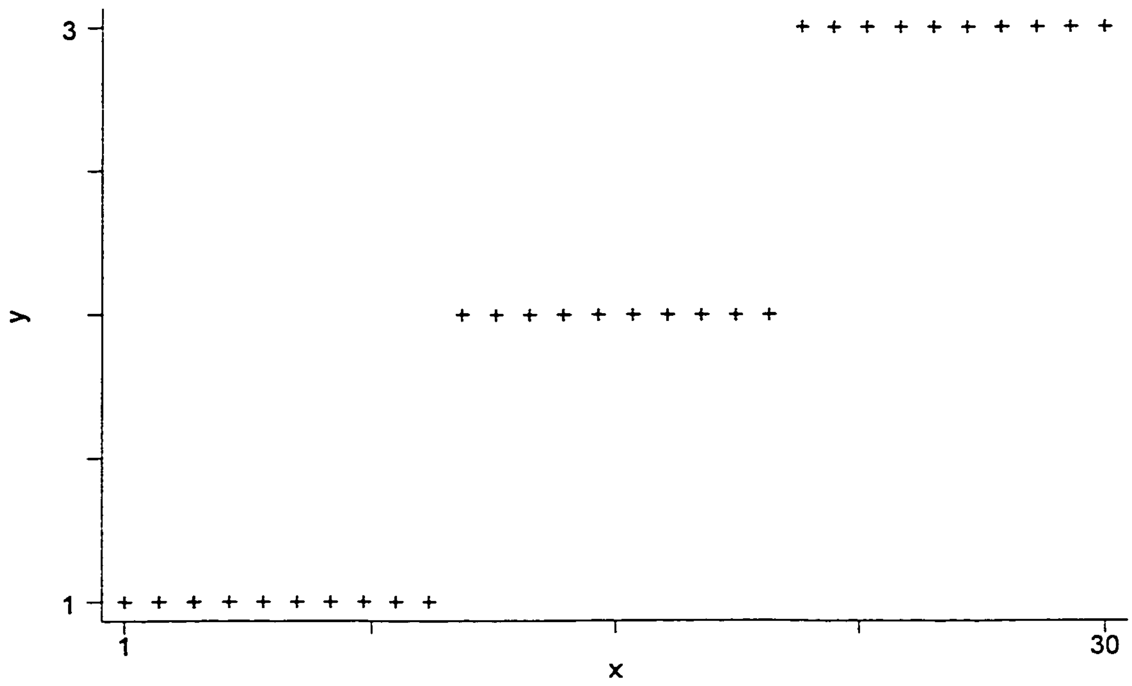

Figure 5.3.1 Hypothetical graph showing data that would be ideally suited to controlling by stratification.

Of course, our data were not this ideal, and stratification thus was not an entirely successful technique for controlling confounding. For instance, consider the relationship between log GDP per capita and life expectancy. In Figure 5.3.2, actual data from this study are used to show how stratifying by levels of GDP per capita may not entirely control for GDP per capita as a continuous variable. The steepest slope running the entire length of the graph is the slope ignoring stratification. The three shallower slopes are the slopes for each stratum of income category. Note that the stratum-specific slopes are not zero, so perfect control of confounding is not present, but they are closer to zero than the crude slope. Thus, when we include urbanization in our model and then stratify by income category, we have imperfect controlling of confounding by GDP per capita. Regardless, despite the limitations of stratification in this study as an analytic technique, the usefulness of stratification by low, medium, and high income remains a useful descriptive technique.

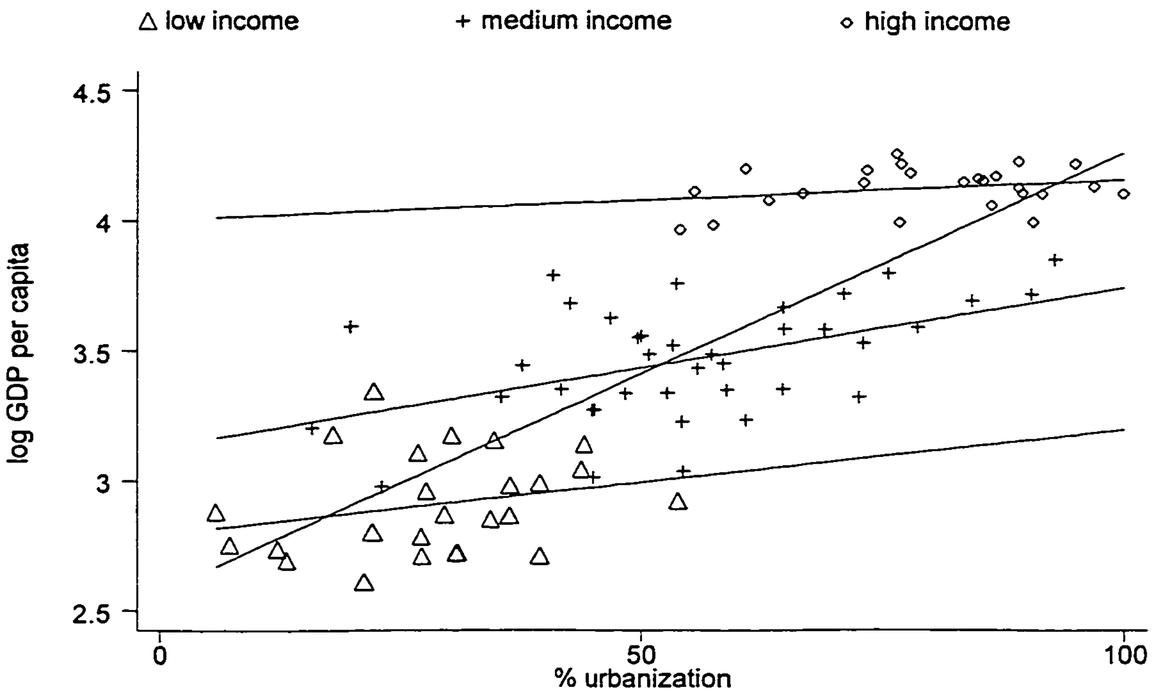

Figure 5.3.2 Relationship between % urbanization and log GDP per capita illustrating that stratification does not completely control for confounding.

From a theoretical point of view, it may be asked whether we should attempt to control for confounding by GDP per capita at all. Under the usual definition of confounding, if we are to consider GDP per capita to be a confounder, it has to be causally related to the outcome in question and be non-causally associated with the other covariates in the model. However, there is an alternative scenario. If the other covariates in the model are causally related to GDP per capita, then it may be inappropriate to control for GDP per capita. This is because, by definition, if GDP per capita is in the causal pathway, it cannot be a confounder. It is most likely, however, that both are true. Most likely, there are multiple causal pathways from our covariates to our outcomes. Some of these pathways would go through GDP per capita and others would not. In this situation, controlling for GDP per capita would reveal the relationship directly from the covariates to the outcome. Leaving GDP per capita completely out of the model would render a slope representing a mix of associations, some of which mediate through GDP per capita and some of which do not. An additional complication is that we do not know if GDP per capita should be in the causal pathway between the other covariates and the outcome, or if the other covariates should be between GDP per capita and the outcome. In fact, there may be complex feedback loops among all of the variables, further complicating the situation. Figure 5.3.3 is a hypothetical, though not unlikely, situation showing complex relationships among GDP per capita, the other covariates, and health outcomes.

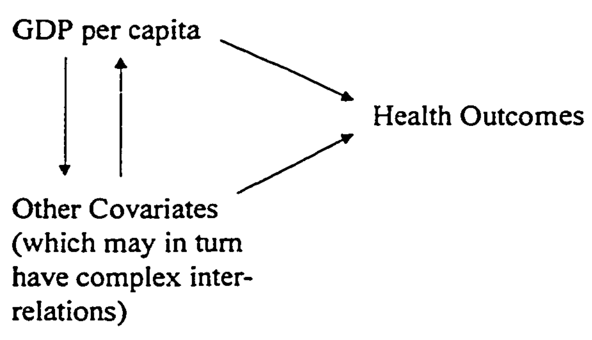

Figure 5.3.3 Hypothetical complex inter-relations among predictors.

Unfortunately, little is known about the precise inter-relationships among environment, economics, and human health. Our approach has resulted in a compromise, wherein we have partially controlled for GDP per capita. For the time being, this is the best compromise that we could make.

5.4 The Meaning of Small Associations

The preceding discussion begs the question of whether the smaller associations that we have noted in the EI variables are "real". That is, if we have not adequately controlled for confounding by GDP per capita, can we be certain that the association between, say, high disturbance and life expectancy, would not disappear? Further, if it did disappear, is this because GDP per capita was in the causal pathway? We believe that the smaller associations detected by this study should be interpreted with care. Although the amount of explained variance in each model is reasonably high, the associations between the EI variables and the selected health outcomes are consistently quite small. Had we more adequately controlled for confounding by GDP per capita, those smaller associations might disappear. On the other hand, they might also become larger or remain the same. Despite the uncertainty regarding what would happen if we added additional variables or were better able to control for the associations already in the models, it seems prudent to regard small associations with some suspicion.

Could we not use p-values to decide whether the associations seen are "real"? The meaning of statistical significance in this study is questionable. We have tried to avoid the use of p-values or any of the trappings of statistical significance in our model building because doing so would require that we postulate a "super-population" of all "possible" countries. Statistical significance refers to the probability that the parameters of a randomly chosen sample taken from a population represent the true parameters of that population. In this study, we have used all of the countries of the world as our starting point; that is, we have used the entire world population, not a random sample. It is true that there are missing values in our data set. Thus, strictly speaking, we are not using the entire world population. However, neither have we randomly chosen a sample from the world population. Instead, the "sample" that we have used is based on whether we had appropriate data available. This is not random, but rather is likely to reflect certain conditions, such as not having adequate infrastructure to collect data, being in an area too war-ravaged to collect data, or, paradoxically, not being rich enough to collect one's own data, but not being quite poor enough to warrant special attention by United Nations agencies. All of these possibilities are, in turn, potentially in the causal pathways to health.

Because of the undesirability of postulating some super-population of possible countries, we feel that it is best to consider our results not as statistics *per se*, but rather as population parameters. Of course, doing so limits the scope of our data to the countries in the models, such that we cannot generalize to the countries for which data are missing.

In summary, tests of statistical significance are of limited use and cannot be used to give us confidence in our model. Instead, we consider effect size an important indicator of confidence in our results, because associations of larger magnitude are less likely to be eliminated by the inclusion of additional covariates in the regression models.

5.5 Outliers

Sometimes the association between two variables may be large and therefore, at first glance, important. For instance, consider the relationship between high disturbance and log infant mortality among high income countries. The standardized regression coefficient is -0.835 suggesting a very strong relationship. However, Figure 5.5.1 shows us that the strength of that relationship is largely determined by a single outlier: Israel.

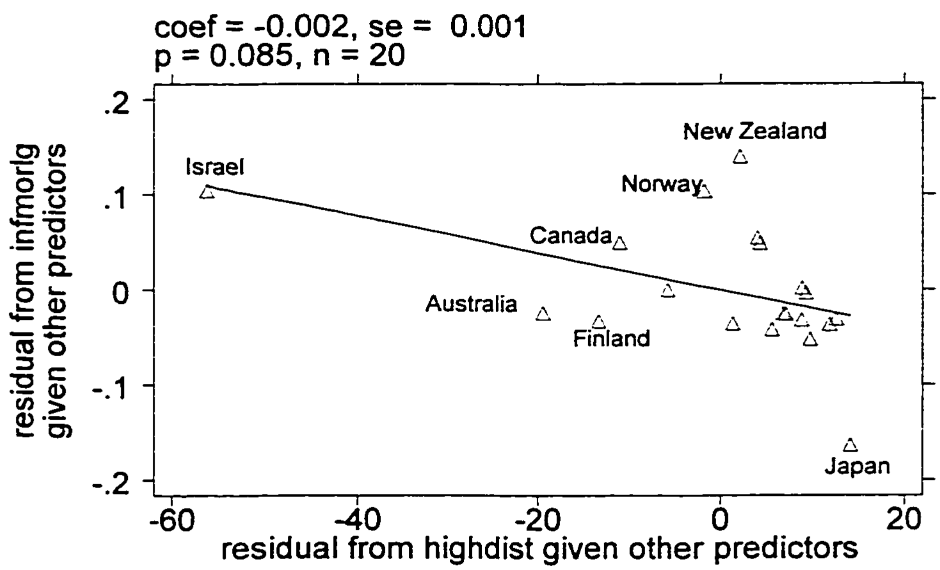

Figure 5.5.1 The relationship between high disturbance and log infant mortality among high income countries (adjusted for other model covariates).

Although a thorough study of outliers is beyond the scope of this thesis, such an analysis, particularly by individuals with expertise in world geography and politics would be useful. For instance, in the above example, why is Japan's infant mortality rate so low and why is New Zealand's so high? Clearly, a variable could be found and added to the model that would explain that considerable difference.

It is interesting to note that there is a tendency for the same outliers to show up repeatedly in each analysis. In the model developed with life expectancy as the outcome (Figures 4.9.7 to 4.9.10), Sri Lanka, Sierra Leone, and Guinea-Bissau consistently appeared as outliers among the low-income countries. Senegal, Congo, South Africa, Gabon, and Costa Rica were consistently found as outliers among the medium-income countries. Iceland, Kuwait, Japan, and New Zealand often were found as outliers in the high-income category. We interpret this to mean that there is something about these countries that is different from the others in their respective income categories. This information could be used to find additional covariates to add to our model.

5.6 Exploratory Analysis - Summary

It should be noted that the intent of this study is exploratory in nature. We have found some small associations between increasingly highly disturbed land areas and each of our three human health outcomes. We have found similar associations with annual change in forest cover rates or amount of forest remaining and all of our human health outcomes. The associations between the EI variables and the health outcomes have been adjusted for the effect of several, quite powerful, confounders. We also have found that some high profile environmental indicators, namely percent of species threatened and land protection, have no association with health outcomes. In addition, we have noted that we have some reservations about the adequacy of the models that we have developed. It is likely that more sophisticated modeling techniques, such as linear structural equation modeling, would further clarify the complex relationships among our variables.

5.7 Limitations of Using Aggregate Data

The unit of analysis in this study is not the individual, but rather aggregations of individuals at the country level. One of the limitations of such a study is that, although we believe that some of the associations found among our variables at the population level are ultimately mediated at the individual level, we cannot extrapolate our results to individuals. After all, life expectancy is a population characteristic, but it is still mediated by the death of individuals. At the same time, it would be quite difficult to ascertain cause and effect relationships between ecological variables, such as percent of species threatened or land disturbance, and life expectancy. For variables such as these, it is more appropriate to consider the relationships at the aggregate level since these variables may have little or no meaning at the individual level.

There are good reasons for why we cannot extrapolate our aggregate data results to individuals, even if we did have an adequate causal hypothesis at the individual level. The aggregate study design sits low on the hierarchy of epidemiologic study designs in terms of its ability to contribute to causal inference. One of the main limitations of aggregate data studies is that we cannot be sure that the individuals who are exposed are the same ones who contract the disease. The aggregate data reflect only the average level of exposure and disease for the group, whereas a very different relationship may exist between individual exposure and disease. Sometimes, the association seen at the aggregate level is, in fact, the reverse of that seen when further individual-level studies are conducted. Essentially, the aggregate-level variable is measuring a different underlying construct than the corresponding individual-level variable. For this reason, we cannot extrapolate results from aggregate data studies directly to individual risks. This is not especially problematic in this study, since the ultimate aim is not to extrapolate to individuals, but rather to learn about characteristics unique to populations.

The most important limitation of this study is that our models are almost surely misspecified. We do not know enough about these population-level interactions to have much certainty about the completeness of our models. Since aggregate data studies often are conducted when little is known of the exact exposure-disease relationship, model misspecification probably is quite common.

Another problem with aggregate data studies is that the investigator generally, of necessity, obtains his or her data from several different sources. Obtaining data from multiple sources can result in an unknown error owing to the incomparability of covariates from different data sources. In some cases, the data obtained from developing countries, or from countries with political motivations for falsifying their data, may be so poor that United Nations organizations may fail to acknowledge them as "official" data. In this study, poor data were excluded from all analyses.

Chapter 6 - Interpretation

This study, like most in epidemiology, is based on past experience. Under the best of conditions, the prediction of events based on models is fraught with peril, generally because future patterns of outcome assume continuing exposures similar to those that gave rise to the models in the first place. An example of this is the prediction of new HIV infections in Africa by the World Bank (World Bank. 1993). The World Bank envisions optimistic and worst case scenarios based on different sets of assumptions. The optimistic scenario is that the incidence rate will decrease by a small percentage by the year 2000, whereas the worst case scenario predicts a doubling of the incidence rate. This example illustrates that extrapolations of even very well-studied phenomena suffer from strong reliance on *a priori* assumptions that can result in widely differing predictions. Regardless of the accuracy of the model, extrapolation involves assumptions that, by definition, cannot be known with much certainty.

The prediction of completely new events is still less certain. For instance, no matter how good a mathematical model of infectious disease dynamics we might have had in the 1970s, no one could have predicted the emergence of AIDS in the 1980s. One could perhaps have predicted that the conditions were right for the emergence of a pathogen (Morse 1993), but one could not have known either the actual identity or the timing of the emergence.

In the case of environmental degradation and, possibly, environmental collapse, it seems inevitable that the current trends in measures of EI are leading us in a dangerous direction. There is overwhelming evidence of diminishing biodiversity (Karr and Chu 1997; World Resources Institute et al 1998), profound soil degradation (Kendall and Pimentel 1994; Pimentel and Hawthorn 1981) and acidification (Kane 1996; World Resources Institute et al 1998), global warming (Kaufmann and Stearn 1997; Tunali 1996), and ozone depletion (World Resources Institute et al 1996; World Resources Institute et al 1998), among other problems. In addition, perhaps the most powerful evidence for a future ecological collapse is from an energy and materials throughput analysis. Ecological footprint analysis has revealed that, given current technology, we cannot sustain our current levels of consumption (Rees 1996b; Wackernagel and Rees 1996). To make matters worse, all indicators suggest that with increasing global population and the economic and technological advancement of the developing world, global consumption is going to increase. In addition, the global economy enables rich and powerful countries to extract resources from anywhere in the world to sustain their consumption habits, meaning that an ecological collapse will not simply be an isolated, local event, as it might have been in the past, but rather a global one (Rees 1996b; Wackernagel and Rees 1996).

The question might be asked, then: why do we continue perpetuating these dangerous trends? This study may provide a partial answer to that question. Our results show that there is a separation of consumption from consequence. According to this study, generally speaking, industrialization, urbanization, conversion of land to human use, and destruction of other species are either good for, or unrelated to, human health. At least in the short term, countries are rewarded for environmental destruction with ever-improving human health. If, however, the environment were no longer able to sustain an intense level of human activity, because of an environmental collapse, human health would surely decline rapidly.

6.1 Catastrophic versus Gradual Effects

To interpret this study, it is important to distinguish between two quite distinct phenomena: a catastrophic, high-inertia environmental collapse versus a gradual decline in EI resulting in more subtle health effects.

The health impact of a catastrophic environmental collapse would be enormous, inherently unstable, and impossible to model because there is no prior experience upon which to base such models. Indeed, epidemiologic models are not needed to show that the loss of nature's life support services, and the consequent period of chaos, would be devastating to human life.

On the other hand, if the decline of the ecosphere can be assumed to be a gradual extension of current trends without any sudden collapse, then epidemiology is well-equipped to discern which environmental factors currently are most closely associated with human health. The definition of health, in this case, could be as broad or as narrow as the investigator wishes. It could include the physical, emotional, and/or social dimensions of health. The question of how to measure the relationship between EI and human health thus can be answered only if it is taken as given that the consequences of a decline in EI would occur on a predictable trajectory.

6.2 Lack of an Integrated Ecological Model

We have chosen measures of EI, where data are available, based on the definitions articulated by the Global Ecological Integrity Project (see section 1.2) and related them to three general health outcomes. However, a fundamental link in the chain of evidence is missing. A detailed model that integrates humans into earth's ecological systems is needed which can link elements of EI to human health. With such an integrated model, researchers would have the equivalent of a biological basis that could be used to link specific measures of EI with specific disease outcomes. Fortunately, the Agroecosystem Health Project has attempted to define, describe, and evaluate the health of agroecosystems, including these systems' human components (Smit et al 1998). This has provided a road map that ecologists, coupled with sociologists and epidemiologists, could use to create an integrated model for much larger natural ecosystems.

Although research that transcends disciplinary boundaries is rare (Norgaard 1992), it is necessary if an integrated model is to be developed. This must go beyond having the disciplines simply sit next to one another; instead they must generate novel concepts by synthesizing the various disciplinary knowledge bases. More and more in epidemiology, for example, links are made with the social sciences to facilitate research into the social determinants of health (Rosenfield 1992). The synthesis of sociology and epidemiology and the success of this research has greatly advanced the social determinants of health agenda. The Agroecosystem Health Project has synthesized much of the literature on interdisciplinary research and offers a useful framework for advancing that agenda (Smit et al 1998).

6.3 How Much Integrity?

The results of this study may provide some answers as to why the environment is often a secondary consideration for policy-makers. This study shows that ecological disintegrity is "disconnected" from human health. There is a trade-off between improving conditions for human life and depleting/destroying the environment. So far, that trade-off has favoured continued development at the expense of the environment.

How much integrity is necessary for human health? The ultimate answer must come from ecology because it is the same as whatever amount will forestall the collapse of the biosphere. The models developed for this study are based on past events and are inadequate for predicting catastrophic events. In terms of the less apocalyptic effects on human health, it seems that the current articulation of EI has little relation to human health. With the help of an integrated ecological model, however, our model could be refined with additional variables, and with data gathered over as many years and/or decades as possible into the future. It should be recognized that in the absence of a guiding ecological model, our exploratory model is almost certainly misspecified.

6.4 Some Ethical Issues

Issues of justice may arise from the tentative findings of this study. The world population is increasing and with it the demand for resources. The largest increases in population and in resource consumption will be in the developing world. Should developed countries be telling developing countries to rein in their population and their economic development to prevent ecological collapse? Should the rich countries of the world rein in their consumption? The developed world has long enjoyed the benefits of economic and social development. Not least among those benefits is an increasing life span. Some might argue that such benefits have been had at the expense of environmental degradation in regions of the world well beyond the borders of the beneficiaries (i.e., via large and globally distributed ecological footprints). Can the rich countries of the world deny these benefits to the developing countries of the world?

This study cannot answer these questions but, if the principle of social justice is important, then it would seem that the developed nations of the world need to help their under-developed cousins. Specifically, developed nations need to provide benefits to the developing world, perhaps in the form of technology transfers, assisting them to improve their standard of living without undue damage to the environment. For example, if the developed world would like equatorial countries to preserve their rain forests for the good of the planet, then richer countries should provide food and other benefits so that forested land does not have to be cleared for agriculture. In this way, everyone would be sharing in the responsibility to maintain and even to restore the planet's essential services.

Chapter 7 - Conclusions and Recommendations

Aggregate data studies provide the most feasible approach for studying human health effects associated with diminishing EI at this time. Indeed, most studies of phenomena related to ecological disintegrity have been aggregate data studies. Thus, most human health studies relating to ecological disintegrity have been hypothesis-generating studies and should be recognized as such. Proper understanding of the hierarchical nature of epidemiologic inference as well as the limitations of aggregate data analysis will improve the conclusions derived from these studies.

Solid epidemiologic science is a prerequisite to gaining the public trust and, if convincing relationships between human health and ecological disintegrity are found, we believe that its potential to impact public policy would be great. Most notably, a great leap forward in epidemiologic studies related to EI would require an ecological model integrating natural and human systems. Until then, only weak models will be derivable in the absence of a dramatic shift in any of the relevant health outcomes.

There are two quite separate issues regarding EI and human health, catastrophic collapse and a gradual decline in EI potentially resulting in less dramatic health effects. The latter issue is that which is addressed by this study. That is, does EI as articulated by the Global Ecological Integrity Project have any association with human health outcomes? The simple answer is that we cannot yet be sure. Ours is but a single study, and the first to address EI in relation to human health. More detailed modeling needs to be considered, and so do alternative study designs. It is likely that more sophisticated modeling techniques, such as linear structural equation modeling, would further clarify the complex relationships among our variables. Our model could be refined with additional variables, and as more data on EI become available, studies could be undertaken at a lower level of analysis, perhaps at the county level instead of at the country level. This would enable the investigator to have much more control over data quality, and could perhaps even lead to a better understanding of the exposures involved.

Figure 7.1 uses the lessons learned in this study to depict the problem areas that could be addressed with additional studies and different types of data.

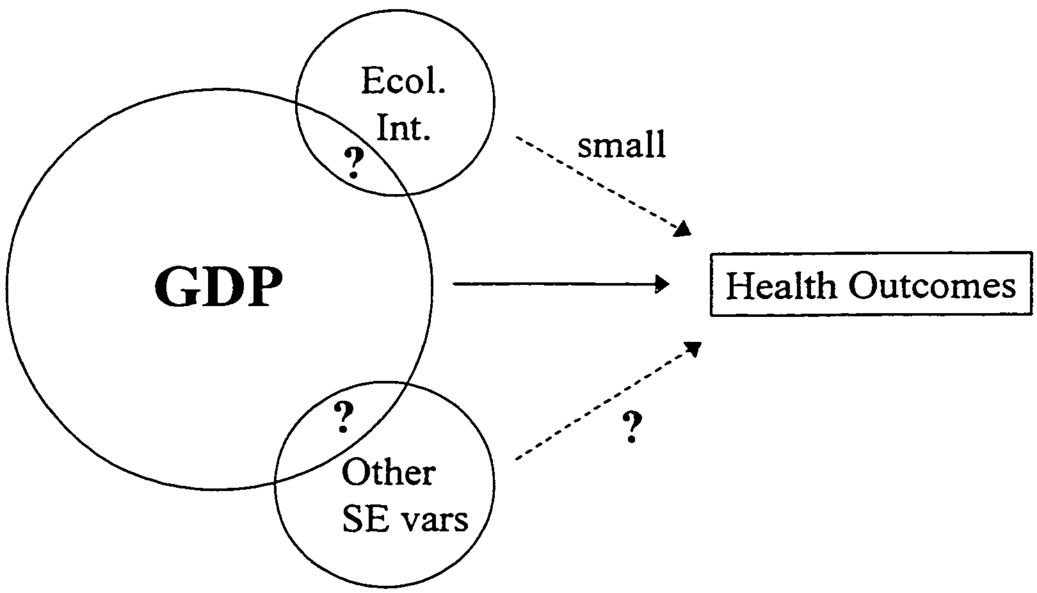

Figure 7.1 Areas for future research.

The question marks indicate where additional research should be aimed. GDP was a problem in this study because it was so overwhelming that we could not be certain how to model it. The overlapping circles represent strong collinearity between GDP and EI and GDP and other socio-economic variables. Certainly, GDP is a common tool to measure wealth, but it may be too all-encompassing to be used in detailed modeling. The contribution of this study is that we have shown that, at least for cross-sectional data from the recent past, the relationship between EI and human health has been small or non-existent. An improvement to this study would be the refinement of the models with additional predictors, which may be teased from a closer examination of the outlier countries.

For this study, without a clear causal mechanism, and using only cross-sectional data, the literal interpretation of coefficients (e.g., X lives lost per acre of wild land domesticated) would be wrong and, simply put, absurd. However, we can see clearly that *at this time* socio-economic considerations far outweigh issues of environmental degradation in the public mind, especially in developing countries, and also seem to dominate decision-making. In developed countries, we can see the beginnings of negative health consequences associated with environmental degradation. In developing countries, however, poverty is such an important determinant of health that the subtle associations between diminishing EI and human health are not noticeable as yet, if they ever will become noticeable. Longitudinal data studies may be able to discern more subtle trends and/or cyclical patterns.

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Appendices

Appendix 1: Ecological footprint ranking of 52 nations

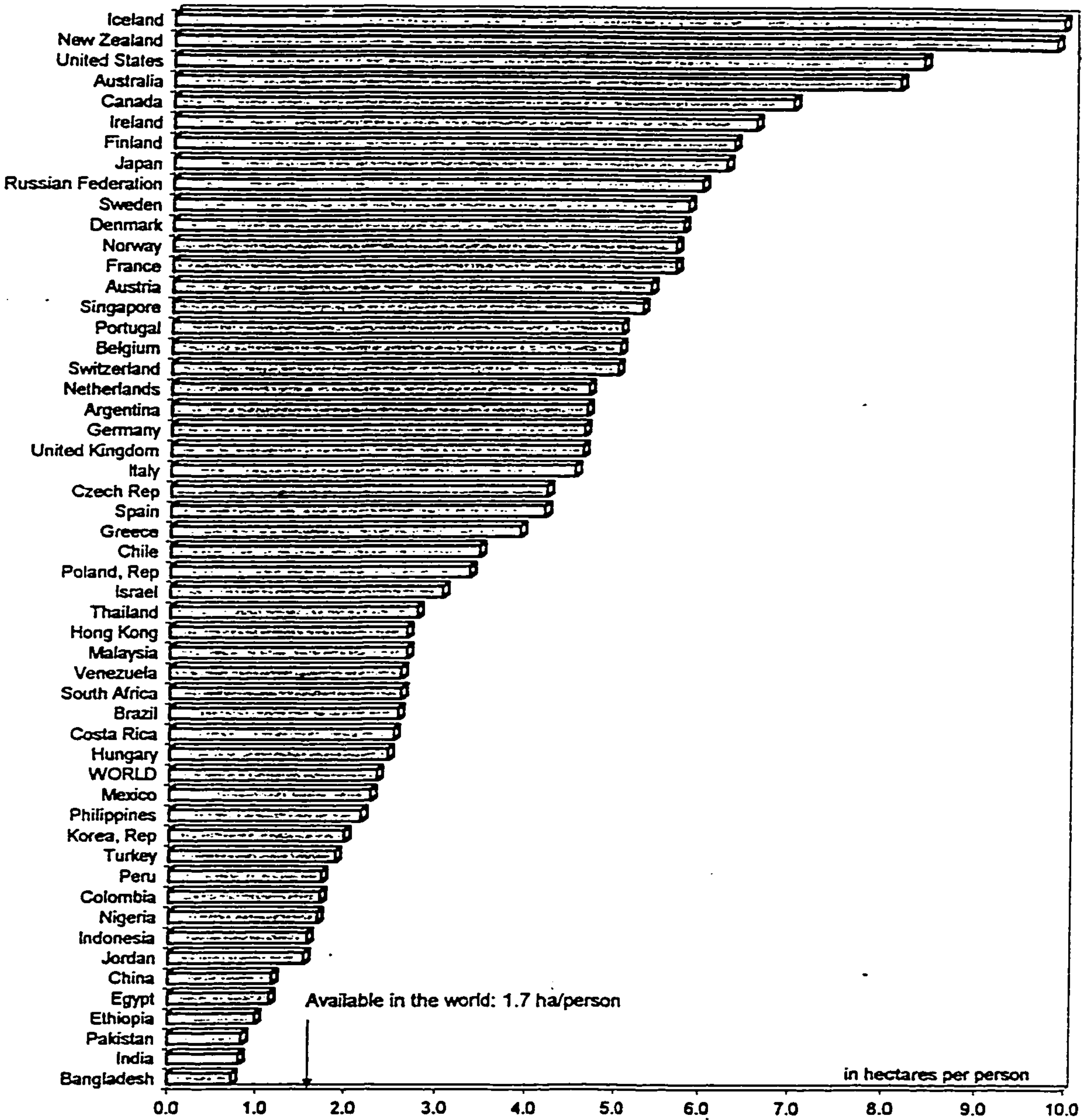

Figure from Wackernagel M, Onisto L, Linares AC, Falfan ISL, Garcia JM, Guerrero AIS, and Guerrero MGS. Ecological Footprint of Nations: How much nature do they use? – How much nature do they have? Report to the Earth Council, Costa Rica, 1997.

Appendix 2: List of all available variables on World Resources Institute database diskettes (1996-97)

Variables in the WRI database are classified according the various subheadings. They are listed here alphabetically by subheading.

Atmosphere and Climate

Carbon Dioxide Emissions from Solid Fuels
Carbon Dioxide Emissions from Liquid Fuels
Carbon Dioxide Emissions from Gas
Carbon Dioxide Emissions from Gas Flaring
Carbon Dioxide Emissions from Cement Manufacture
Total Carbon Dioxide Emissions from Industry
Carbon Dioxide Emissions from Industry per capita
Carbon Dioxide Emissions from Bunker Fuels
Carbon Dioxide Emissions from Land Use Changes
Methane Emissions from Solid Waste
Methane Emissions from Coal Mining
Methane Emissions from Oil and Gas Production
Methane Emissions from Wet Rice Agriculture
Methane Emissions from Livestock
Total Methane Emissions from Anthropogenic Sources
Atmospheric Concentrations of Carbon Dioxide
Atmos. Concentrations of Carbon Tetrachloride (CCI4)
Atmos. Concentrations of Methyl Chloroform (CH3CCI3)
Atmos. Concentrations of CFC-11(CCI3F)
Atmos. Concentrations of CFC-12 (CCI2F2)
Atmos. Concentrations of CFC-113 (C2CL3F3)
Atmos. Concentrations of Total Gaseous Chlorine
Atmos. Concentrations of Nitrous Oxide
Atmos. Concentrations of Carbon Dioxide
Total Global Carbon Dioxide Emissions
Global Carbon Dioxide Emissions from Solid Fuels
Global Carbon Dioxide Emissions from Liquid Fuels
Global Carbon Dioxide Emissions from Gas Fuels
Global Carbon Dioxide Emissions from Gas Flaring
Global Carbon Dioxide Emissions from Cement Mfg
Global Carbon Dioxide Emissions Per Capita
Global Carbon Dioxide Emissions from Bunker Fuels
Sulfur Dioxide (SO2) Emissions
Nitrogen Oxide (NO2) Emissions
Common Anthropogenic Pollutants - Carbon Monoxide
Common Anthropogenic Pollutants - Particulate Matter
Common Anthrop. Pollutants - Volatile Org. Compounds
Carbon Dioxide Emissions (Selected Countries)
Methane Emissions (Selected Countries)
Nitrous Oxide Emissions (Selected Countries)

Biodiversity and Protected Areas

Protected Areas by IUCN Categories
Large Protected Areas (IUCN I-V) By Size
Resource & Anthropological Reserves (VI-VIII) - Number
Resource & Anthropological Reserves (VI-VIII) - Area
Heritage Sites (Natural and Mixed) - Number
Heritage Sites - Area
Percent of National Land Area Protected
Protected Marine & Coastal Areas - Number
Protected Marine & Coastal Areas - Area
Biosphere Reserves - Number
Biosphere Reserves - Area
Wetlands of International Importance - Number

Wetlands of International Importance - Area
Map Units of Low Human Disturbance - Percent
Map Units of Medium Human Disturbance - Percent
Map Units of High Human Disturbance - Percent
CITES Reporting Requirement Met
Live Primates - Net Imports
Live Primates - Net Exports
Cat Skins - Net Imports
Cat Skins - Net Exports
Live Birds - Net Imports
Live Birds - Net Exports
Reptile Skins - Net Imports
Reptile Skins - Net Exports
Live Cacti - Net Imports
Live Cacti - Net Exports
Live Orchids - Net Imports
Live Orchids - Net Exports
Length of Coastline
Maritime Area - Shelf to 200m Depth
Maritime Area - Exclusive Economic Zone
Coastal Marine Species Info
Marine Habitats
Mammal Species Info
Bird Species Info
Reptiles Species Info
Amphibian Species Info
Freshwater Fish Species Info
Plant Species Info
Botanical Gardens and BGCI Members
Habitat - extent of all forest
Habitat - all forest (loss)
Habitat - extent of dry forest
Habitat - dry forest (loss)
Habitat - extent of moist forest
Habitat - moist forest (loss)
Habitat - extent of savannah/grassland
Habitat - savannah/grassland (loss)
Habitat - extent of desert/scrub
Habitat - desert/scrub (loss)
Habitat - extent of wetland/marsh
Habitat - wetland/marsh (loss)
Habitat - extent of mangroves
Habitat - mangroves (loss)

Economic Indicators

Gross National Product (Current US$)
Gross National Product Per Capita (Current US$)
Distribution of Gross Domestic Product-Agriculture
Distribution of Gross Domestic Product - Industry
Distribution of Gross Domestic Product - Services
Official Development Assistance
Gross National Product (Constant US$)
Gross Domestic Product (Current LC)
Gross Domestic Product (Current PPP)
Gross Domestic Product (Current US$)
Gross Domestic Product Per Capita (Current US$)
Gross Domestic Product Average Annual Growth Rate
Gross Domestic Product (Constant PPP)
Gross Domestic Product per Capita (Constant PPP)
Total External Debt (stocks)
Disbursed Public and Publicly Guaranteed Debt
Total Debt Service Paid
Long-term Debt Disbursements (Current Borrowing)
Exports of Goods & Non-Factor Services
Imports of Goods and Non-Factor Services
Current Govt Expenditure
Currency Conversion Factors (Exchange Rate)
Commodity Price Indexes
Commodity Prices

Energy and Materials

Total Commercial Fuel Production
Commercial Energy Production--Solid Fuel
Commercial Energy Production--Liquid Fuel
Commercial Energy Production--Gaseous Fuel
Commercial Energy Production--Geothermal
Commercial Energy Production--Hydroelectric
Commercial Energy Production--Nuclear
Total Electrical Production

Commercial Energy Consumption--Total
Commercial Energy Consumption--Per Capita
Energy Exports
Energy Imports
Commercial Energy Consumption--Gas
Commercial Energy Consumption--Electricity
Commercial Energy Consumption--Solid Fuel
Commercial Energy Consumption--Liquids
Traditional Fuel Consumption
Crude Oil Reserves (proved recoverable)
Natural Gas Reserves
Hard Coal Reserves
Soft Coal Reserves
Uranium Reserves
Hydroelectric Resources
Industrial Waste in Selected Countries
Annual Municipal Waste Generation - Total
Annual Municipal Waste Generation - Per Capita
Municipal Waste - Organic as Percent of Inorganic
Municipal Waste - Paper & Cardboard - % of Total Weight
Municipal Waste - Plastic - % of Total Weight
Municipal Waste - Glass - % of Total Weight
Municipal Waste - Metals - % of Total Weight
Municipal Waste - Other - % of Total Weight
Municipal Waste Disposal - Landfill
Municipal Waste Disposal - Incineration
Municipal Waste Disposal - Other
Production - Bauxite
Consumption - Aluminum
Production - Cadmium
Consumption - Cadmium
Production - Copper
Consumption - Copper
Production - Lead
Consumption - Lead
Production - Mercury
Consumption - Mercury
Production - Nickel
Consumption - Nickel
Production - Tin
Consumption - Tin
Production - Zinc
Consumption - Zinc
Production - Iron Ore
Consumption - Iron Ore
Production - Steel Crude
Consumption - Steel Crude
Reserves - Copper
Reserves - Lead
Reserves - Tin
Reserves - Zinc
Reserves - Iron Ore
Reserves - Manganese
Reserves - Nickel
Reserves - Chromium
Reserves - Cobalt
Reserves - Molybdenum
Reserves - Tungsten
Reserves - Vanadium
Reserves - Bauxite
Reserves - Titanium
Reserves - Lithium
Metal Reserves Index
Value of Copper Reserves
Value of Lead Reserves
Value of Tin Reserves
Value of Zinc Reserves
Value of Iron Ore Reserves
Value of Manganese Reserves
Value of Nickel Reserves
Value of Chromium Reserves
Value of Cobalt Reserves
Value of Molybdenum Reserves
Value of Tungsten Reserves
Value of Vanadium Reserves
Value of Bauxite Reserves
Value of Rutile Reserves
Value of Ilmenite Reserves
Total Value of Reserves
Value of Reserves Index

Food and Agriculture

Agriculture: Production Index Per Capita
Agriculture: Production Index
Food Prod Index
Food: Per Capita Production Index
Cereals, Total Area Harvested
Roots and Tubers, Production
Cereals, Total Production
Roots and Tubers, Area Harvested
Arable & Permanent Cropland
Irrigated Land
Total Fertilizer consumption
Total Agricultural Tractors in use
Agricultural Harvesters in use
Arable Land

Permanent cropland
Fertilizer - Production
Fertilizer- Imports
Fertilizer- Exports
Cattle Stocks
Sheep Stocks
Goat stocks
Pig Stocks
Equines (Horses, mules, asses)
Buffalo Stocks
Camel Stocks
Poultry (Chickens, Ducks, and Turkeys)
Grain Fed to Livestock as % of Total Grain Consumption
Cereals - Imports
Cereals- Exports
Total Trade in Oils
Pulses- Exports
Pulses - Imports
Cereals - Receipts
Cereal Donations by Donors
Butter-oil Receipts & Donations
Vegetable Oil Receipts & Donations
Vegetable Oil Donations
Skimmed Milk Receipts & Donations
Other Dairy Products by Donors
Other Dairy Products by Recipients & Donors
Total Labor Force
Agricultural Labor Force

Human Development

Total Population
Female Population
Male Population
Population Density
Mean Rate of Population Growth
Annual Growth Rate of Labor Force
Total Economically Active Population, 1950-2025
Females as Percentage of Total Labor Force
Labor Force - Percent in Agriculture
Labor Force - Percent in Industry
Labor Force - Percent in Services
Percent Unemployment - Male
Percent Unemployment - Female
Crude Birth Rate
Life Expectancy at Birth (both sexes)
Total Fertility Rate
Population Below Age 15
Population aged 15-64
Population Aged 65 and over
Life Expectancy at Birth (Females)
Life Expectancy at Birth (Males)
Female Population
Female Population Aged 15-49
Births Per Age Group
Life Expectancy - Females as Percentage of Males
Crude Death Rate
Infant Mortality Rate
Under-5 Mortality Rate
Maternal Mortality
Children Suffering from Wasting and Stunting 1980-93
Daily per Capita Calorie Supply
Access to Safe Water Urban and Rural
Urban Connections to Safe Water Source
Access to Sanitation: Urban and Rural
Urban Household Connections to Sanitation Service
Total Urban Population
Urban Population Percent
Urban Growth Rates
Rural Growth Rates
Total Rural Population
Total People in Absolute Poverty
Rural People in Absolute Poverty
Urban People in Absolute Poverty
Urban Dependency Ratio
Rural Dependency Ratio
Number of Cities Greater than 750,000
Percent population living in cities of at least 750,000
People in Cities of at least 750,000
Automobile Registrations
Urban Population in Coastal Cities
Air Pollution in Selected Cities, 1989-94
India: City Indicators, 1993
Literacy-Adult Female
Literacy-Adult Male
Total Primary School Enrollment
Gross Primary School Enrollment
Literacy - Females as Percent of Males
Mean Years of School for Females Age 25 and Above
Mean Years of School for Males Age 25 and Above

Oral Rehydration Therapy Use
Infants with Low Birth Weight
1-Yr-Olds Fully Immunized Against TB, DPT, Polio, Measles
Total Expenditure on Health
Births Attended by Trained Health Personnel
Contraceptive Prevalence (Method)
Average Age of First Marriage-Female
Average Age of First Marriage - Male
Year Women Received Vote
Number of Urban Females per 100 Males
Number of Rural Females per 100 Males
Households Headed by Women

Land Cover and Forests

Land Area
Arable & Permanent Cropland
Population Density
Permanent Pasture
Forest and Woodland
Other Land
Total Area
Domesticated Land as % of Land Area
Natural Forest Extent 1990 and Annual Change 1980-90
Extent of Plantations 1990 and Annual Change 1980-90
Extent of Total Forest
Total Forest - Deforestation, 1981-90
Forest & Other Wooded Land '90 & Ann. Chg 1980-90
Extent Annual Logging Closed Broadleaf Forest, 1981-90
Annual Logging of Closed Broadleaf Forest %, 1981-90
Ann Logging Closed Brdlf For: % Primary Forest, 1981-90
Roundwood Production
Fuelwood Production
Industrial Roundwood Production
Sawnwood and Sleepers Production
Wood-based panel production
Paper and paperboard production
Roundwood trade
Roundwood Exports
Roundwood Imports
Rain Forest Extent
Moist Deciduous Forest Extent
Hill and Montane Extent
Dry Deciduous Forest Extent
Very Dry Forest Extent
Desert Forest Extent
Rain Forest - % annual change 1981-90
Moist Deciduous Forest - % annual change 1981-90
Hill and Montane Forests - % annual change 1981-90
Dry Deciduous Forest - % annual change 1981-90
Very Dry Forest - % annual change 1981-90
Desert Forest - % annual change 1981-90

Water and Oceans

Annual Internal Renewable Water Resources
Water Resources per capita
Annual River Flows To and From Other Countries
Annual Water Withdrawals - Amount
Annual Water Withdrawals - Percentage
Annual Water Withdrawals per Capita
Annual Water Withdrawals - by Sector
Primary Wastewater Treatment
Secondary Wastewater Treatment
Tertiary Wastewater Treatment
All Wastewater Treatments
Goods Loaded - Crude Petroleum
Goods Unloaded - Crude Petroleum
Goods Loaded - Petroleum Products
Goods Unloaded - Petroleum Products
Goods Loaded - Dry Cargo
Goods Unloaded - Dry Cargo
Offshore Annual Production - Oil
Offshore Annual Production - Gas
Offshore Proven Reserves - Oil
Offshore Proven Reserves - Gas
Marine Fishery Production by Region
Marine Fish Catch by Region

Cephalopods Catch by Region
Crustaceans Catch by Region
Freshwater Catch by country
Marine Catch by Country
Aquaculture Production - Freshwater Fish
Aquaculture Production - Diadromous Fish
Aquaculture Production - Marine Fish
Aquaculture Production - Crustaceans
Aquaculture Production - Molluscs
Aquaculture Production - Other
Fish Consumption per Capita
Fish Supply

Appendix 3: Countries included in stratified analyses – Life expectancy as outcome

Low GDP per capita (n=39)

Albania
Bangladesh
Benin
Burkina Faso
Burundi
Central African Republic
Chad
China
Cote d'Ivoire
Equatorial Guinea
Ethiopia
Ghana
Guinea
Guinea-Bissau
Guyana
Honduras
India
Kenya
Lao People's Dem Rep
Madagascar
Malawi
Mali
Mauritania
Mongolia
Mozambique
Nepal
Nicaragua
Niger
Nigeria
Pakistan
Rwanda
Sierra Leone
Sri Lanka
Tanzania
Togo
Uganda
Viet Nam
Zambia
Zimbabwe

Medium GDP per capita (n=45)

Algeria
Argentina
Belize
Bolivia
Botswana
Brazil
Bulgaria
Cameroon
Chile
Colombia
Congo
Costa Rica
Dominican Rep
Ecuador
Egypt
El Salvador
Gabon
Greece
Guatemala
Hungary
Indonesia
Jamaica
Jordan
Korea, Rep
Malaysia
Mexico
Morocco
Oman
Panama
Papua New Guinea
Paraguay
Peru
Philippines
Poland, Rep
Romania
Senegal
South Africa
Suriname
Swaziland
Thailand
Trinidad and Tobago
Tunisia
Turkey
Uruguay
Venezuela

High GDP per capita (n=24)

Australia	Ireland	Spain
Austria	Israel	Sweden
Belgium	Italy	Switzerland
Canada	Japan	United Arab Emirates
Denmark	Kuwait	United Kingdom
Finland	Netherlands	United States
France	New Zealand	
Germany	Norway	
Iceland	Portugal	

Appendix 4: Countries included in stratified analyses – Infant mortality as outcome

Low GDP per capita (n=29)

Bangladesh
Burkina Faso
Central African Rep
China
Cote d'Ivoire
Ethiopia
Ghana
Guinea
Guinea-Bissau
Guyana
Honduras
India
Kenya
Lao People's Dem Rep
Madagascar
Malawi
Mali
Mauritania
Nepal
Nicaragua
Niger
Nigeria
Pakistan
Sri Lanka
Tanzania
Uganda
Viet Nam
Zambia
Zimbabwe

Medium GDP per capita (n=35)

Algeria
Argentina
Bolivia
Botswana
Brazil
Bulgaria
Cameroon
Chile
Colombia
Costa Rica
Dominican Rep
Ecuador
Egypt
Greece
Guatemala
Hungary
Indonesia
Jamaica
Jordan
Korea, Rep
Malaysia
Mexico
Morocco
Panama
Peru
Philippines
Poland, Rep
Romania
Senegal
South Africa
Thailand
Tunisia
Turkey
Uruguay
Venezuela

High GDP per capita (n=20)

Australia
Austria
Belgium
Canada
Denmark
Finland
France
Germany
Ireland
Israel
Italy
Japan
Netherlands
New Zealand
Norway
Portugal
Spain
Sweden
United Kingdom
United States

Appendix 5: Countries included in stratified analyses – Low birth weight as outcome

Low GDP per capita (n=51)

Bangladesh	Guinea-Bissau	Niger
Bolivia	Haiti	Nigeria
Bulgaria	Honduras	Pakistan
Burkina Faso	India	Papua New Guinea
Cameroon	Indonesia	Paraguay
Central African Rep	Jordan	Philippines
China	Kenya	Romania
Colombia	Lao People's Dem Rep	Rwanda
Congo	Madagascar	Senegal
Cote d'Ivoire	Malawi	Sierra Leone
Dominican Rep	Mali	Sri Lanka
Ecuador	Mauritania	Tanzania
Egypt	Mongolia	Togo
El Salvador	Morocco	Viet Nam
Ghana	Mozambique	Yemen
Guatemala	Myanmar	Zambia
Guinea	Nicaragua	Zimbabwe

High GDP per capita (n=32)

Algeria	France	Spain
Argentina	Greece	Switzerland
Austria	Jamaica	Thailand
Belgium	Japan	Trinidad and Tobago
Botswana	Korea, Rep	Tunisia
Brazil	Lebanon	Turkey
Canada	Malaysia	United Kingdom
Chile	Mexico	United States
Costa Rica	Panama	Uruguay
Denmark	Peru	Venezuela
Finland	Portugal	