THREE ESSAYS ON THE ENVIRONMENTAL KUZNETS CURVE FOR WATER POLLUTION

by

ALEXI THOMPSON

B.A., Auburn University, 2003
M.S., Auburn University, 2008

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2012

Abstract

This dissertation is composed of three chapters each investigating the Environmental Kuznets Curve (EKC) for water pollution. The first chapter looks at downstream dependence, the second chapter looks at the effect water abundance has on an EKC for water pollution, and the third chapter looks at different ways to control for population across countries in an EKC empirical model. Of particular note a theoretical model is developed in the first chapter that links directly with the empirical EKC model and marginal effects of consumption and effort on pollution are derived. This model specification may be particularly useful in future EKC studies. In general, there is some evidence of an EKC although it appears to depend on the country.

THREE ESSAYS ON THE ENVIRONMENTAL KUZNETS CURVE FOR WATER POLLUTION

by

ALEXI THOMPSON

B.A., Auburn University, 2003
M.S., Auburn University, 2008

A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2012

Approved by:

Major Professor
Jeff Peterson

Abstract

This dissertation is composed of three chapters each investigating the Environmental Kuznets Curve (EKC) for water pollution. The first chapter looks at downstream dependence, the second chapter looks at the effect water abundance has on an EKC for water pollution, and the third chapter includes ideas from the first two chapters to an expanded dataset. Of particular note a theoretical model is developed in the first chapter that links directly with the empirical EKC model and marginal effects of consumption and effort on pollution are derived. This model specification may be particularly useful in future EKC studies. In general, there is some evidence of an EKC although it appears to depend on the country.

Table of Contents

List of Figures

List of Tables

Acknowledgements

I would like to thank my major professor, Dr. Jeff Peterson, for his support and guidance during my years at Kansas State University. I would also like to thank the other members of my committee; Dr. Tian Xia, Dr. Jason Bergtold, Dr. Yang Ming Chang, and Dr. Walter Dodd for their helpful comments and suggestions as well as Dr. John Crespi. I would also like to thank my parents, Henry Thompson and Madeline Simos. They have always encouraged me to follow my dreams, whether that be earn a Ph.D. in Economics at Kansas State University or run a bar on a Greek island. I would also like to thank my dad for his economics suggestions; having a dad that’s an economics professor is a valuable source of information. I would also like to thank my mom for cooking lots of Greek food while visiting me in Manhattan. I would also like to thank Koichi Yamaura, Maureen McGuigan, and Merci Paulamuleni for their friendship. A huge thanks to Dr. Smith and Dr. Roop for helping put my T.O.S. on its A.S.S. Most of all, I would like to thank my girlfriend Leidy Pena for her support and arepas.

Dedication

I would like to dedicate this dissertation to my parents, Henry Thompson and Madeline Simos.

Chapter 1. Introduction

This dissertation is composed of three essays investigating the Environmental Kuznet's Curve (EKC) for water pollution. The EKC describes the relationship between environmental degradation and income per capita as an inverted U-shape. This implies that as a country grows rich, it may be able to grow out of environmental problems. The maximum point of the EKC curve is called the turning point and indicates the level of income where pollution degradation is maximized and above which pollution levels lessen. The most common air pollution indicator is CO_2 and the most common water pollution indicator is biochemical oxygen demand (BOD), which measures the amount of oxygen required by organisms to break down waste.

Originally thought to be primarily an empirical phenomenon, a few theoretical reasons for the EKC have been brought forth. Grossman and Kreuger (1991) decompose production in an economy into scale, technique, and composition effects. The scale effect means that increased production leads to increased pollution given no change in technology. The technique effect stipulates that economic growth will result in production and utilization of more efficient technologies that are typically less polluting. The composition effect says that as a country develops, economies shift from manufacturing based activities to more service oriented activities that are less polluting. An EKC relationship between pollution and income may result if technique and composition effects become larger than scale effects over time.

Yet another explanation for the existence of an EKC relates economic growth to changes in consumption patterns. As citizens become wealthier they begin to demand environmental quality as reported by Antle and Heidebrink (1995).

The EKC relationship was first discovered by Grossman and Kreuger (1991) in their study of the effects of NAFTA on the environment. Since this initial study, the EKC topic has become prominent in the environmental economic literature. The paper by Grossman and Krueger has been cited over 2000 times. Since the initial study, however, results from empirical studies have not been conclusive about the existence of the EKC. Some studies find evidence of the EKC, while others do not. Studies that find evidence of an EKC yield very different turning points. Perhaps its persistence in the literature is due to inconclusive evidence. Over time, theoretical and empirical EKC models have become more sophisticated. A brief look at the chronology of the EKC literature illustrates both the increase in sophistication of the empirical methods of the papers and continued debate over the possible existence of the EKC.

One of the first EKC studies by Shafik and Bandyopadhy (1992) was particularly influential because their results were presented in the 1992 *World Development Report*. They estimate quadratic, cubic, and log linear models on a number of environmental indicators including lack of clean water, lack of urban sanitation, ambient levels of suspended particulate matter (SPM), ambient sulfur oxides, dissolved oxygen in rivers, fecal coliform in rivers, deforestation, carbon emissions per capita, and municipal waste per capita for 149 countries between the years 1960 and 1990. Not all years are covered for each pollution indicator. Results indicated an EKC for suspended particulate matter with a turning point of $3280 annual per capita income and SO_2 with a turning point of $3670 annual per capita income in 1987 US dollars. Access to clean water and sanitation improve with increased income per capita. The results were not quite as consistent with the EKC hypothesis for river quality indicators, as dissolved oxygen monotonically increases with increased income and fecal coliform follows an

N-shaped curve, implying that at very high income, fecal coliform increases. Carbon emissions per capita also do not improve with increasing incomes, as well.

Technological improvements were introduced with a time trend and increased environmental degradation at every income level. The authors conclude it may be possible for certain countries to grow out of certain environmental problems but that in general policy changes are required.

Panayotou (1993) estimated EKC air pollution and deforestation in a cross sectional study. Air pollutants include sulfur dioxide SO_2, nitrous oxide NO_X, and suspended particle matter SPM. Results indicate evidence in support of EKCs for pollutants with a turning point between \$800 and \$1200 for deforestation and between \$3800 and \$5500 (in 1985 dollars) for air pollutants. He also finds countries transition from industrial to service oriented activities once per capita reaches \$10,000.

Perman and Stern (2003) were among the first authors to consider time series properties of the data. They perform individual country and panel country unit root tests to estimate an EKC for sulfur emissions for 74 countries spanning 31 years. They do not find evidence of an EKC in their study using the same dataset as Grossman and Krueger (1991).

Citing Perman and Stern (2003), Granda, Perez, and Munoz (2008) also consider the time series properties of the data in their EKC water pollution study on a panel data set of 46 countries for the years 1980-2000. They test for unit roots and cointegration, and include trade intensity as an additional explanatory variable. Preliminary tests revealed their data were difference stationary. They run an error correction model that includes lagged independent regressors on the left hand side. The authors do not find evidence of an EKC for the countries in their panel dataset.

Lee, Chiu, and Sun (2010) use the generalized method of moments (GMM) approach across 97 countries for the period of 1980-2001 in their EKC study on water pollution. The pollution indicator is BOD. The GMM method is employed to deal with simultaneity bias between income per capita and pollution levels. By using the lag of income per capita, simultaneity is addressed because current pollution does not affect past income per capita. The Sargan test and second-order serial correlation test are used to test the instruments. No evidence of a global EKC is found. The authors divide the countries into the following groups: America, Africa, Asia and Oceania, and Europe. There is no EKC evidence for the groups of Africa, Asia or Oceania. The authors find evidence of EKC in America and Europe (in their quadratic specification) with turning points of $13,956 annual per capita income and $38,221 annual per capita income, expressed in year 2000 dollars, respectively.

This brief literature review illustrates the differences in estimation methods, additional explanatory factors, and results in EKC studies. Other functional forms that have been used include non-parametric and semi-parametric approaches (Li Wang 2010; Zapata and Paudel 2009). Additional explanatory variables that will be discussed in greater detail in the chapters include political institutions (Bhatarrai and Hammig 2001), civil liberties (Paudel et.al 2005), and population density (Panayotou 1997). Despite the advances in econometrics employed in EKC studies, results tend to vary depending on estimation technique, data, and additional explanatory variables used in the empirical studies.

While not addressing all the problems associated with EKC studies, the chapters in this dissertation contribute to the EKC literature on water pollution. The chapters explore two new additional explanatory variables that have been overlooked in water pollution EKC studies, namely upstream country income and water abundance.

Is it environmentally beneficial or detrimental to be downstream from a rich country? This is the question I attempt to answer by explicitly including upstream country income (and its square) in an EKC model for downstream water pollution. Annual water pollution levels represent river pollution and upstream and downstream countries are EU members. Policy implications are relevant because EU members are under the same governing body. Results indicate for this dataset upstream incomes do not matter.

The second variable I introduce to the water EKC literature is water abundance. Attitudes toward water pollution may differ across countries depending on how scarce is the country's water supply. Results verify the importance of including water abundance, as its inclusion eliminates any evidence of an EKC.

In addition to introducing these new variables to EKC literature, I derive a theoretically tractable model that may have broad appeal in EKC studies. While a large number of EKC studies have either used empirical or theoretical models, I am unaware of published studies that have linked the two approaches. I specify a utility function that is quadratic in consumption and environmental effort and a pollution function that is quadratic in consumption and environmental effort. Results from the empirical model are linked to the theoretical pollution function to derive second order marginal effects of consumption and environmental effort on pollution.

The rest of this introduction includes objectives of each chapter, a discussion of the data, and description of econometric methods. The three chapters follow. Finally a discussion of results and general conclusion is reached.

Objectives of Study

Chapter 2 Downstream Dumping

Chapter 2 has two objectives. The first is to address downstream dependence in an EKC regression for river pollution. Data consists of a panel of upstream and downstream European countries. Conceptually, biochemical oxygen demand (BOD), the water pollution indicator in a downstream country, is a function of its income (Y_D) and the income of its upstream neighbor (Y_U), $BOD = f(Y_D, Y_U)$

The empirical model takes the form

$$BOD_{it} = \beta_i + \beta_1 Y_D + \beta_2 Y_D^2 + \beta_3 Y_U + \beta_2 Y_U^2$$

where all variables are expressed in levels. From a policy standpoint, this paper tests whether it is beneficial to be downstream from a developed country.

The second objective of the study is to connect a theoretical EKC model to the empirical EKC model. Although several theoretical papers and empirical EKC studies have been published, the two have not been linked to my knowledge. The theoretical model, loosely based on a model by Andreoni and Levinson (2001), stipulates consumer utility U is a function of consumption C and environmental effort E, $U = f(C, E)$, subject to the income constraint, $Y = C + E$ where Y is income. The main difference between the present model and Andreoni and Levinson (2001) is that the utility function I propose is quadratic and theirs is a Cobb-Douglas utility function. The quadratic utility function preserves diminishing marginal effects of consumption and environmental effort on utility and is theoretically tractable unlike the Cobb-Douglas specification. By linking the theoretical and empirical models, I am able to derive parameter estimates for consumption and environmental effort for agents in the upstream and downstream countries.

Downstream pollution decreases with economic growth in the upstream country. There is evidence of an EKC in the downstream country with respect to income per capita in the downstream country. The theoretical model developed may be used in future EKC studies to derive second order effects of consumption and effort on utility.

Chapter 3 Water Abundance and the EKC for Water Pollution

The objective of Chapter 3 is to address the omitted variable problem in water EKC studies by including water abundance in an empirical specification. Estimates and turning points from the basic EKC model,

$$BOD_{it} = \beta_{0i} + \beta_1 Y_{it} + \beta_2 Y_{it}^2$$

are compared to the model

$$BOD_{it} = \beta_{0i} + \beta_{1i} Y_{it} + \beta_{2i} Y_{it}^2 + \beta_{3i} W_{it} + \beta_{4i} W_{it}^2 + \beta_{5i} YW_{it} + \beta_{6i} YW_{it}^2$$

that includes water abundance W_{it} and interaction terms. The variables are in natural logarithms. The results of the basic model indicate an EKC for water pollution. However, when water abundance is included there is no EKC and water abundance has a U-shaped relationship with pollution. This implies that water scarce countries take better care of their water supply, possibly, due to the high marginal cost of water pollution. Pollution increases in water abundant countries, possibly because the marginal cost of pollution is low. This result suggests future water EKC studies should include water abundance in their empirical EKC models.

Chapter 4 Accounting for Population in an EKC for Water Pollution

This chapter explores the role of population in empirical studies. While panel estimation should control for differences across countries as more populated countries should pollute more, more pollution may not lead to more pollution per capita. I estimate two models each of which control for population in different ways. One model accounts for population by expressing BOD in per capita terms and the second model regresses BOD on population using the residual in the EKC regression. The Akaike Information Criterion (AIC) reveals the second model is preferred to the first model. In addition, although both models reveal an EKC, the turning points are vastly different. Future EKC studies can benefit by testing EKC models that control for population in different ways.

Data

The water pollution indicator used in all three chapters is biochemical oxygen demand (BOD), which is measured in kilograms per day reported as an estimated yearly average. BOD data comes from the website EarthTrends (2007) that defines BOD as “the amount of oxygen that bacteria in water will consume in breaking down waste.” The site goes on to explain that the more oxygen used to break down waste, the less oxygen there is available for aquatic life so that a polluted river will have a high level of BOD. These BOD estimates are from industrial waste and do not include agricultural runoff. The yearly data runs from 1980 to 2000.

All income per capita data comes from the Penn World Tables (2009). The base year is 2005.   Water abundance variables in Chapters 3 and 4 come from EarthTrends (2007) and the Penn World Tables (2009). First, total water availability is measured in cubic kilometers for all fresh water within a country’s border. Water availability is divided by population data from Penn World Tables (2009) to convert water availability to per capita terms. The same dataset is used in chapters 2 and 3. Population data comes from Penn World Tables (2009).

Methods

I discuss estimation in each of the chapters, but as a brief overview of all three chapters I use pooled mean group (PMG) estimation developed by Pesaran (1995, 1999) and Pesaran (1999). This recently developed technique is well suited for panel data with large time and cross section (country) dimensions. PMG estimation is more flexible than traditional fixed effects (FE) panel estimation by accounting for heterogeneity in estimates across countries.

Chapter 2 - Downstream Dumping

The environmental Kuznets curve (EKC) describes the relationship between income per capita and environmental degradation as an inverted U-shape. At initial stages of economic development and low income per capita, environmental degradation increases with income because increased production leads to pollution. Eventually, the environmental problems are redressed as demand for environmental quality increases with rising income.

The goal of the present study is to examine downstream dependence in an environmental Kuznet's curve for water pollution. The data includes annual BOD and incomes from six EU countries for the years 1980-2000. Only in recent EKC studies has spatial dependence been accounted for (Rupasingha et. al 2004; Maddison, 2006; Auffhammer , Bento, and Lowe 2009). These studies usually involve spatial econometric methods with the assumption that you can pollute your neighbors and they can pollute you. However, in the case of river water pollution, emissions are unidirectional, travelling downstream.

The present study adds to the present EKC literature in the following ways. First, a theoretical framework motivates downstream dependence in an EKC model. Regression results indicate upstream income is not an important explanatory variable for this dataset. This paper improves upon the existing literature by linking a tractable theoretical model to an empirical EKC model. Despite the vast literature on the EKC, this appears to be the first attempt to link theoretical and empirical parameters of the EKC model. Linking the two models is relevant for devising policy and should be useful in future EKC studies.

Literature Review

There are a number of possible explanations that have been proposed as reasons for the Kuznets curve. Grossman and Kreuger (1991) decompose production in an economy into scale, technique, and composition effects. The scale effect means that increased production leads to increased pollution given no change in technology. The technique effect stipulates that economic growth will result in production and utilization of more efficient technologies that are typically less polluting. The composition effect says that as a country develops, economies shift from manufacturing based activities to more service oriented activities which are less polluting. An EKC relationship between pollution and income may result if technique and composition effects become larger than scale effects as economies grow.

Regulation has also been offered as a reason for the EKC relationship between pollution and income (Grossman and Kreuger 1995). Developed economies are more environmentally stringent than developing economies. Once a certain level of GDP is reached, consumers begin to demand a cleaner environment, making more stringent environmental policies politically popular.

The displacement hypothesis and pollution haven hypothesis have also been used as reasons for the EKC. De Bruyn and Heintz (1999) describe the displacement hypothesis as asymmetries in consumption and production structures due to trade openness that may “displace” pollution intensive industries from developed economies to developing economies. Along similar lines, poor countries may have a comparative advantage in the production of pollution intensive goods because industries are less regulated. Polluting industries may relocate to developing country to avoid environmental laws, the “pollution haven hypothesis” (Stern, Common, and Barbier 1996). In short, there are a number of competing theories for the EKC, all of which have valid arguments and none of which have been resoundingly confirmed or refuted.

Grossman and Kreuger (1991) first proposed the idea of the EKC in their study of the impacts of North American Free Trade Agreement (NAFTA) on Mexico. The authors use the

Global Environment Monitoring Systems (GEMS) database that covers many site specific pollution indicators in countries around the world. They look at three air pollution indicators, SO_2, suspended particulate matter, and dark matter (smoke in the air). Their dataset covers the years 1977, 1982, and 1988. The number of countries represented varies by pollution indicator. Grossman and Kreuger also include several dummy variables such as a time trend, communist country, land use (commercial, industrial, or residential), etc. Random and fixed effects are estimated and results indicated an inverted U-shaped relationship between GDP per capita and SO_2 and dark matter. Turning points (at 5% significance level) are \$4630 annual per capita income for SO_2, and around \$5000 annual per capita income for dark matter (in 1985 US dollars). Although no EKC is found in the case of suspended particles, even initial economic growth has a negative impact on this environmental indicator. An interesting note is that although their research was conducted to study the effects of NAFTA, Mexico was not included in the data due to data limitations. Policy implications for Mexico are based upon results for countries similar in development stage as Mexico. One of the shortcomings of EKC articles is that evidence of an EKC (regardless of the environmental indicator) seems to depend heavily on the countries included in the study (Stern 2004). Therefore, the policy implications for Mexico discussed in this paper may not be robust.

Shafik and Bandyopadhy (1992) wrote a particularly (important and) influential paper on the EKC because their results were presented in the 1992 *World Development Report*. They estimate quadratic, cubic, and log linear models on a number of environmental indicators including lack of clean water, lack of urban sanitation, ambient levels of suspended particulate matter (SPM), ambient sulfur oxides, dissolved oxygen in rivers, fecal coliform in rivers, deforestation, carbon emissions per capita, and municipal waste per capita for 149 countries between the years 1960 and 1990. Not all years are covered for each pollution indicator. Results indicated an EKC for suspended particulate matter with a turning point of $3280 annual per capita income and SO_2 with a turning point of $3670 annual per capita income in 1987 US dollars. Access to clean water and sanitation improve with increased income per capita. The results were not quite as consistent with the EKC hypothesis for river quality indicators, as dissolved oxygen monotonically increases with increased income and fecal coliform follows an N-shaped curve, implying that at very high income fecal coliform increases. Carbon emissions per capita also do not improve with increasing incomes. Technological improvements were introduced with a time trend and increased environmental degradation at every income level. The authors conclude it may be possible for certain countries to grow out of certain environmental problems but that in general policy changes are required.

Since the initial studies mentioned above, there have been a number of published articles on the EKC. A number of environmental quality indicators have been studied including air quality (Shafik and Bandyopadhyay, 1992), deforestation (Cropper and Griffiths 1994; Panayotou 1993) and water quality (Shafik and Bandyopadhyay 1992; Granda, Perez, and Munoz 2008) with mixed findings. Vincent et. al (1997) does not find an EKC for six air pollutants in his study of Malaysia. Perman and Stern (2003) do not find evidence of an EKC in their study of the same dataset as Grossman and Krueger accounting for time series properties of the dataset. Panayotou (1993;1995) estimated EKC's for SO_2, NO_X, SPM, and deforestation in a cross sectional study involving developing countries and finds EKC's for the three pollutants.

Initial studies by Grossman and Kreuger pointed out the need for additional explanatory variables in EKC studies. The most basic EKC model regresses an environmental quality indicator on income and its square, $E = \alpha_0 + \alpha_1 Y + \alpha_2 Y_2 + \varepsilon$, where E is the environmental quality indicator (usually in per capita terms), Y is GDP per capita, Y^2 is the square of GDP per capita, and ε is a stochastic error term. Income per capita and its square are usually in natural logs. However, many studies point out other explanatory variables may affect or lead to the existence of an EKC. Other variables include political institutions (Bhatarrai and Hammig 2001), civil liberties (Paudel et.al 2008), and population density (Panayotou 1997).

EKC Problems

EKC studies have been the subject of various criticisms (Stern et. al 1996, Stern 2004, Arrow et. al 1995, Ekins 1997). Stern et. al (1996) provides a concise summary of seven major problems with EKC studies including econometric problems. Most EKC studies assume that economic growth affects environmental quality but not vice versa. Studies by Cole et. al (1997) and Holtz-Eakin and Seldon 1995, use a Hausman Test and conclude that income per capita is an exogenous determinant of pollution levels. The use of ambient or emissions data largely depends on the type of study. For example, emissions data may be more appropriate when measuring cross-country effects. Stern et. al (1996) explains that majority of people earn less than mean income, so median rather than mean income is more appropriate in EKC studies. Stern (2004) lists heteroskedasticity, simultaneity, omitted variable bias, and cointegration issues as major econometric problems in EKC literature. Heteroskedasticity arises from cross country panel nature of the data. Previous articles find residuals from high income per capita countries are heteroskedastic (Stern 1996, Schmalensee et al. 2002). Stern (2002) employs feasible GLS to account for heteroskedasticity, thus improving fit. As previously mentioned Cole et al. (1997) and Hotlz Eakin (1995) test for simultaneity using the Hausmann Test and find income is exogenous. Omitted variable bias is a serious concern (Stern and Common 2001) although recent articles have included several additional explanatory variables (Panayotou 1997; Paudel et.al 2005).

Panel data sets that include a long time series have seldom performed the proper diagnostic tests pertinent to time series modeling (Perman and Stern 2003). Perman and Stern (2003) estimate an EKC for sulfur emissions for 74 countries spanning 31 years and perform individual country and panel country unit root tests. They find no evidence of an EKC when accounting for the time series properties of the data. Testing of various functional forms including non-parametric and semi-parametric models (Li 2010; Zapata and Paudel 2009), decomposition models (de Bruyn 1997; Viguier 1999), and frontier modeling have added to the sophistication of EKC modeling in recent years. Results in recent papers still seem largely dependent on the countries included in the model.

Wagner (2008) discusses additional econometric problems of EKC articles. He mentions that in the recent articles addressing time series properties (Perman and Stern 2003) that the applied unit root tests assume cross sectional independence. These “first generation” methods are not appropriate in EKC panel models. Second-generation panel unit root tests account for cross sectional dependence which, he shows, are more appropriate in EKC studies. Another overlooked problem is that income per capita and its square have different asymptotic properties. To address these problems, Wagner used factor models and the finding of stationary de-factored GDP. Wagner estimated an EKC for carbon emissions for a balanced panel of 100 countries from the years 1950-2000. An EKC for carbon emissions was present under first generation panel unit root tests but no evidence was found under the more appropriate second generation panel unit root tests.

Mythili and Mukherjee (2010) look for an EKC in their study of river pollution in India. Disaggregated pollutants include BOD and Dissolved Hydrogen Ions (pH) for ten major rivers across India. The years covered are 1990-1991 and 2005-2006. Major environmental regulations were imposed in 1992 so the two time series studied reflect pre and post regulation periods. They estimate a random effects model with GLS estimation and an AR(1) disturbance; explanatory variables include a cubic GDP per capita term, a time dummy reflecting post and pre-1992 time periods, an urbanization ratio (ratio of urban population total population), and an industry category dummy accounting for the most polluting industries. Two models are estimated for each pollutant, the latter including the time dummy. Results indicated an s-shape for BOD and pH (although income is not statistically significant in the case of pH). The s-shaped EKC indicates an initial decrease in BOD as income rises, then increase once income hits a certain level, then a subsequent decrease after the second turning point. In both models for BOD, the industry category dummy is statistically significant, urbanization positively influences BOD levels in the second model, and contrary to expectations, the policy dummy had a positive effect on BOD and pH levels. They reason the positive effect of the environmental policy was due to a “policy shift in favor of small-scale industries” and conclude the need for various environmental regulations including command-and –control, and incentive-based policies to limit pollution in India.

Lee et al. (2010) use the generalized method of moments (GMM) approach across 97 countries for the period of 1980-2001 in their EKC study on water pollution. The pollution indicator is BOD. The GMM method is employed to deal with simultaneity bias between income per capita and pollution levels. By using the lag of income per capita, simultaneity is addressed because current pollution does not affect past income per capita. The Sargan test and second-order serial correlation test are used to test the instruments. The authors find no evidence of a global EKC. The authors then divide the panel of countries into five groups: America, Europe, Africa, Asia, and Oceania. No EKC for water pollution is found in Africa, Asia, or Oceania. They do find evidence of an EKC in America and Europe (in their quadratic specification) with, turning points of $13956 annual per capita income and $38221 annual per capita income, expressed in year 2000 dollars, respectively.

Lin and Liscow (2009) tackle simultaneity and omitted variable problems in their EKC study for water pollutants. The authors also focused on the political mechanisms of the EKC. Using the GEMS database, they collected data on eleven water pollution indicators including BOD, chemical oxygen demand (COD), lead, mercury, etc. Indices on political rights and civil liberties are retrieved from Freedom House to account for political mechanisms. A cubic GDP term is added to the model. Other explanatory variables include the age dependency ratio, total debt service, the amount of GDP that comes from manufacturing, water temperature, and population density. The countries represented in the data vary according to pollutant, with the most countries (67) represented in the model for dissolved oxygen and the fewest number of countries (18) in the model for total nickel. To reduce problems associated with simultaneity bias, Lin and Liscow use debt service and age dependency ratio as instruments for GDP per capita. The instrumental variables are used in regressions where GDP per capita is found to be endogenous by the Durbin-Wu-Hausman test. The authors also account for the presence of heteroskeadsticiy by generalized method of moments estimation (GMM). Results indicate evidence of an inverted U-shaped EKC for seven of eleven pollutants (BOD, COD, arsenic, cadmium, lead, nickel, fecal coliform) and political institutions affect five of the eleven pollution indicators (dissolved oxygen, nitrate, arsenic, cadmium, and mercury).

Barua and Hubeck (2009) look for the presence of BOD and COD for sixteen Indian states using annual watershed data from 1980-2000. Watershed data is averaged from monitoring sites within each state. Their model includes income, its square, and a cubic term. No other explanatory variables are included. Results indicate an EKC for water pollution in four states and an N-shaped curve for eight states with initial turning points of $110 annual per capita income and second turning point of $320 annual per capita income. The authors suggest policy initiatives and the need for more explanatory variables in the conclusion.

Granda, Perez, and Munoz (2008) look for an EKC for BOD on a panel data set of 46 countries for the years 1980-2000. Besides income and its square, they include a trade intensity variable as an explanatory variable. Special consideration is given to the time series properties of the data including individual country and panel unit root and cointegration tests. Preliminary tests revealed their data was difference stationary, and they run an error correction model, which includes lagged independent regressors on the left hand side. The authors do not find evidence of an EKC for the countries in their panel set.

Managi et. al (2009) studied the effect of trade openness on the pollution levels of SO_2, CO_2, and BOD in OECD and non-OECD countries. Their dataset was comprised of SO_2 and CO_2 emissions of 88 countries from 1973 to 2000 and BOD emissions of 83 countries from 1980 to 2000. They decomposed emissions into scale and composition effects. They further considered the endogeneity of income per capita. Income per capita was a function of trade openness, capital-labor ratio, population, and human capital. They addressed the dynamic properties of their data by employing a Generalized Method of Moments (GMM) estimator. Results showed that trade resulted in fewer emissions of all pollutants in OECD countries but an increase in emissions of CO_2 and SO_2 in non-OECD countries. Trade did eventually decrease BOD emissions in non-OECD countries.

Paudel et al. (2005) compared parametric to semi-parametric models in their water pollution EKC study. Watershed data covered 53 parishes in Louisiana from 1985-1999. Pollution indicators include dissolved oxygen, nitrogen, and phosphorus. A cubic term for GDP per capita, a population density variable, and a weighted income variable were included to account for spillover effects. One way and two way fixed and random effects were estimated and compared with each other using the Hausman Test. The spillover effect was accounted for by first calculating the queen contiguity matrix. The one way fixed effects model was found to be the best model by the Hausman Test. The results from the one way fixed effects show EKC relationships for all three pollutants with turning points $11572 annual per capita income, $8508 annual per capita income, and $9145 annual per capita income for nitrogen, phosphorus, and dissolved oxygen respectively. Only dissolved oxygen was statistically significant at the 5% level. A quadratic specification of the one way fixed effects model also revealed EKC relationships for all pollutants; however, phosphorus was the only pollutant statistically significant at the 5% level with a turning point of $7493 annual per capita income. A semi parametric specification was compared with the one way fixed effects model using Hong and White's test and results indicated that only in the case of phosphorus is the semi parametric specification favored over the parametric specification.

Theoretical Model

Although originally purely an empirical phenomenon, a number of theoretical models of the EKC have been recently developed. Infinitely-lived agent models (Lopez 1994; Seldon and Song 1995) and overlapping generation models (John and Pecchenino 1994; McConnell 1997) explain the existence of the EKC. Brock and Taylor (2010) develop the Green Solow Model, an extension of the Solow model including a resource constraint, to explain the EKC. A model developed by Andreoni and Levinson (2001) approaches the EKC from a consumer standpoint and assumes increasing returns to pollution abatement. These authors derive conditions for a turning point.

The model developed in the present paper extends the Andreoni and Levinson model (henceforth A&L) to account for downstream dependence of river water quality between two countries. Before proceeding, it should be noted that spillover and transboundary effects of an EKC (for air and water pollution) have been investigated (Sigman 2002; Helland and Whitford 2003; Maddison 2006; Paudel et. al 2005). Barua and Hubacek (2009) examine water pollution in sixteen Indian states by regressing BOD as a cubic function of income. They consider downstream dependence regressing the residual from their model on the incomes of the upstream states. While some other papers have shown water pollution does flow to downstream countries, I am more concerned with finding whether downstream pollution levels may be redressed with income growth in the upstream country.

A&L consider externalities in their theoretical paper and generalize their model to include many agents. They derive conditions for an EKC assuming Nash equilibrium. The idea is that you can pollute your neighbor and your neighbor can pollute you. However, river pollution is unidirectional. The externality model A&S develop is more relevant in the case of air, lake, or ocean pollution that can travel in any direction.

The A&L model assumes one agent whose utility is a function of consumption and pollution. The following model considers two agents with the utility of the downstream agent a function of pollution from the upstream country.

Consider two agents, agent 1 in the upstream country (U) and agent 2 in the downstream country (D). The utility of agent 1 is a general function of their consumption and pollution,

$$U_U = U(C_U, P_U) \tag{1}$$

and the downstream agent's utility is a function of their consumption and pollution,

$$U_D = U(C_D, P_D). \tag{2}$$

Utility is quasiconcave in C and -P for upstream and downstream agents. Pollution in the upstream country is a function of consumption C_U and environmental effort E_U,

$$P_U = P_U(C_U, E_U) \tag{3}$$

where $\left(\frac{\delta P_U}{\delta C_U}\right) > 0$ and $\left(\frac{\delta P_U}{\delta E_U}\right) < 0$.

Pollution in the downstream country is a function of consumption and environmental effort in the downstream country, plus the fraction of upstream pollution that travels downstream,

$$P_D = P_D(C_D, E_D) + \lambda P_U \tag{4}$$

where $\left(\frac{\delta P_D}{\delta C_D}\right) > 0$ and $\left(\frac{\delta P_D}{\delta E_D}\right) < 0$ Income Y is spent on consumption C and environmental effort E. Prices of C and E are normalized to 1 in the income constraint

$$Y_i = C_i + E_i \tag{5}$$

where i = U, D.

In a specified utility function, agent i maximizes

$$U_i = C_i - z_i P_i \tag{6}$$

where z_i is the constant marginal disutility of pollution. Pollution in the upstream country is specified by A&L as

$$P_U = C_U - C_U^{\alpha} E_U^{\beta} \tag{7}$$

where consumption is directly proportional to pollution. The parameters α and β are assumed to both be less than one. If α+β>1, pollution abatement technology exhibits increasing returns to scale and if α+β<1, pollution exhibits decreasing returns to scale. This functional form implies that if $E_U = 0$, then $P_U = C_U$. The term $C^\alpha E^\beta$ represents a concave abatement function. Consumption and environmental effort affect pollution in the downstream country

$$P_D = \lambda P_U + C_D - C_D^\delta E_D^\varphi. \tag{8}$$

Assume z = 1 in (6). Substitute (8) and (7) into (6) to obtain the objective function for agents 1 and 2. Agent 1 will maximize utility by choosing optimal consumption and environmental effort according to the objective function,

$$U_U = C_U^\alpha E_U^\beta \text{ s.t. } Y_U = C_U + E_U \tag{9}$$

Agent 2 will maximize utility according to

$$U_D = -\lambda P_U + C_D^\delta E_D^\varphi \text{ s.t.} Y_D = C_D + E_D \tag{10}$$

Solving for optimal consumption and environmental efforts for both agents results in

$$C_U^* = (\frac{\alpha}{\alpha+\beta})Y_U \tag{11}$$

$$E_U^* = (\frac{\beta}{\alpha+\beta})Y_U \tag{12}$$

$$C_D^* = (\frac{\delta}{\delta+\varphi})Y_D \tag{13}$$

$$E_D^* = (\frac{\varphi}{\delta+\varphi})Y_D\ . \tag{14}$$

Substitute optimal consumption and environmental effects into (7) and solve for the optimal pollution level in the downstream country,

$$P_D = \lambda\left(\left(\frac{\alpha}{\alpha+\beta}\right)Y_U - \left(\frac{\alpha}{\alpha+\beta}\right)^\alpha \left(\frac{\beta}{\alpha+\beta}\right)^\beta Y_U^{\alpha+\beta}\right) +$$

$$\left(\left(\frac{\delta}{\delta+\varphi}\right)Y_D - \left(\frac{\delta}{\delta+\varphi}\right)^\delta \left(\frac{\varphi}{\delta+\varphi}\right)^\varphi Y_D^{\delta+\varphi}\right) \tag{15}$$

Given the optimal pollution in the downstream country, we can now derive curvature properties of an EKC for downstream water pollution for upstream and downstream countries. Taking first and second derivative of P_D with respect to downstream income Y_D yields

$$\left(\frac{\partial P_D}{\partial Y_D}\right) = \left(\frac{\delta}{\delta+\varphi}\right) - (\delta+\varphi)\left(\left(\frac{\delta}{\delta+\varphi}\right)^{\delta}\left(\frac{\varphi}{\delta+\varphi}\right)^{\varphi} Y_D^{\delta+\varphi-1}\right)$$

(16)

$$\left(\frac{\partial^2 P_D}{\partial Y_D^2}\right) = (\delta+\varphi-1)(\delta+\varphi)\left(\left(\frac{\delta}{\delta+\varphi}\right)^{\delta}\left(\frac{\varphi}{\delta+\varphi}\right)^{\varphi} Y_D^{\delta+\varphi-2}\right) \tag{17}$$

To see the effect of income of the upstream country on downstream BOD, take the first and second derivative of (14) with respect to Y_U:

$$\left(\frac{\partial P_D}{\partial Y_U}\right) = \lambda(\left(\frac{\alpha}{\alpha+\beta}\right) - (\alpha-\beta)\left(\left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\beta}{\alpha+\beta}\right)^{\beta} Y_D^{\alpha+\beta-1}\right)) \tag{18}$$

$$\left(\frac{\partial^2 P_D}{\partial Y_U^2}\right) = \lambda((\alpha+\beta-1)(\alpha+\beta)\left(\left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\beta}{\alpha+\beta}\right)^{\beta} Y_U^{\alpha+\beta-2}\right)) \tag{19}$$

It is more likely that there is not constant marginal disutility of pollution, that is z does not equal one. Regardless, the basic property remains $\alpha + \beta > 1$ for an EKC.

The results depend on the values of α and β for an EKC of downstream pollution with respect to upstream income and δ and φ for an EKC with respect to downstream income. If $\alpha + \beta > 1$, $\left(\frac{\partial^2 P_D}{\partial Y_U^2}\right) < 0$ by equation (19) implying a convex shaped curve between downstream pollution and upstream income per capita. If $\delta + \varphi > 1$, equation (17) implies a convex shape between downstream pollution and downstream income per capita. To derive α, β, φ, δ, C_U^*, C_D^*, E_U^*, and E_D^* the basic EKC effect is estimated as

$$BOD = \alpha_0 + \alpha_1 Y_U + \alpha_2 Y_U^2 + \alpha_3 Y_D + \alpha_4 Y_D^2 + \varepsilon \tag{20}$$

where BOD is biochemical oxygen demand.

Necessary assumptions for linking (15) and (20) include λ = 1 and α + β = 2. There are increasing returns to pollution abatement if α + β = 2, as A&L found for US manufacturers. Comparing (15) to (20) yields the following coefficient estimates:

$$\alpha_1 = (\frac{\alpha}{2}) \tag{21}$$

$$\alpha_2 = (\frac{\alpha}{2})^{\alpha}(\frac{\beta}{2})^{\beta} \tag{22}$$

$$\alpha_3 = (\frac{\delta}{2}) \tag{23}$$

$$\alpha_4 = (\frac{\delta}{2})^{\delta}(\frac{\varphi}{2})^{\varphi} \tag{24}$$

Solving (21) and (23) in terms of α and δ yields:

$$\alpha = 2\alpha_1 \tag{25}$$

$$\delta = 2\alpha_3. \tag{26}$$

Noting

$$\beta = 2 - \alpha \tag{27}$$

$$\varphi = 2 - \delta \tag{28}$$

and substituting (25) and (26) into (22) and (24) to get α_2 and α_4 in terms of α_1 and α_3 yields

$$\alpha_2 = \alpha_1^{2\alpha_1}(1 - \alpha_1)^{2-2\alpha_1} \tag{29}$$

$$\alpha_4 = \alpha_3^{2\alpha_3}(1 - \alpha_3)^{2-2\alpha_3} \tag{30}$$

Unfortunately, the restrictions α + β = 2 and φ + δ = 2 are too restrictive; there are no closed form solutions for β and δ as functions of the α_i's.

To make this model tractable, consider a modified version of the A&L model. By linking the theoretical and empirical model, it is possible to derive marginal values of consumption and environmental effort on utility. Utility is a function of consumption and pollution U = f(C, P). Upstream utility is

$$U_U = \delta_0 C_U - \delta_1 C_U^2 - z_U P_U \tag{31}$$

where z_U is the marginal disutility of pollution assumed equal to one. Upstream pollution is a quadratic function of consumption and environmental effort in upstream and downstream countries,

$$P_U = \gamma_0 C_U - \gamma_1 C_U^2 - E_U + \alpha_2 E_U^2. \tag{32}$$

Plugging the pollution function into the utility function utility $U_U = (\delta_0 - \gamma_0)C_U - (\delta_1 - \gamma_1)C_U^2 + E_U - \alpha_2 E_U^2$. For notational convenience let $(\delta_0 - \gamma_0) = \alpha_0$ and $(\delta_1 - \gamma_1) = \alpha_1$. To ensure that the reduced form utility function is concave, we require $\alpha_0 > 0$ and $\alpha_1 > 0$, which in turn requires the parameter restrictions $\delta_0 > \gamma_0$ and $\delta_1 > \gamma_1$. The upstream agent chooses consumption and effort to maximize utility, subject to the budget constraint $Y_U = C_U + E_U$. The adding-up conditions on the solutions to this problem require the further parameter restriction that $\alpha_0 = 1$.[1] Optimal consumption and effort levels in the upstream country are

$$C_U = \left(\frac{\alpha_2 Y_U}{\alpha_1 + \alpha_2}\right) \tag{33}$$

$$E_U = \left(\frac{\alpha_1 Y_U}{\alpha_1 + \alpha_2}\right) \tag{34}$$

In general $U_D = f(C_D, P_D)$ or

$$U_D = \delta_2 C_D - \delta_3 C_D^2 - z_D P_D \tag{35}$$

Again the z_D represents marginal disutility of pollution in the downstream country, which is assumed equal to one.

---

[1] To see this, note that the solutions to the problem are of the form $c_U^* = \left(\frac{\alpha_0 - 1 + 2\alpha_2 Y_U}{2(\alpha_1 + \alpha_2)}\right)$ and $E_U^* = \left(\frac{1 - \alpha_0 + 2\alpha_1 Y_U}{2(\alpha_1 + \alpha_2)}\right)$. To fulfill the budget constraint that $c_U^* + E_U^* = Y_U$ for all $Y_U > 0$ we must have $\alpha_0 = 1$.

Pollution in the downstream country is

$$P_D = \gamma_2 C_D - \gamma_3 C_D^2 - E_D + \alpha_4 E_D^2 + \lambda P_U^* \tag{36}$$

where λ represents the fraction of upstream pollution that flows downstream. For simplicity, assume λ=1 so that all upstream pollution flows downstream. Substituting (32) into (36) expresses downstream pollution as a function of upstream and downstream consumption and environmental effort,

$$P_D = \gamma_0 C_U^* - \gamma_1 {C_U^*}^2 - E_U^* + \alpha_2 {E_U^*}^2 + \gamma_2 C_D - \gamma_3 (C_D)^2 - E_U + \alpha_2 (E_U^2)^* \tag{37}$$

The potential of diminishing returns to pollution with respect to consumption and environmental effort is preserved from the A&L model.

Substituting (37) into (35) the utility of the downstream citizen is a function of their own consumption and environmental effort as well as upstream consumption and environmental effort,

$$U_D = (\delta_0 - \gamma_0) C_U^* - (\delta_1 - \gamma_1) {C_U^*}^2 + E_U - \alpha_2 E_U^2 + (\delta_2 - \gamma_2) C_D - (\delta_3 -$$

$$\gamma 3CD2+ED-\alpha 4ED2 \tag{38}$$

subject to the constraint on income, $Y_D = C_D + E_D$. As above, impose the parameter restrictions$(\delta_0 - \gamma_0) = 1, (\delta_2 - \gamma_2) = 1$, and let $(\delta_1 - \gamma_1) = \alpha_1$ and $(\delta_3 - \gamma_3) = \alpha_3$. Treating C_U^* and E_U^* as constants and solving for optimal consumption and environmental effort in the downstream country yields

$$C_D^* = \left(\frac{(\alpha_4)}{\alpha_3 + \alpha_4}\right) Y_D \tag{39}$$

$$E_D^* = \left(\frac{\alpha_3}{\alpha_3 + \alpha_4}\right) Y_D \tag{40}$$

Substituting (33), (34), (39), and (40) in the downstream pollution function

$$P_D = \gamma_0 C_U^* - \gamma_1 (C_U^*)^2 - E_U^* + \alpha_2 (E_U^*)^2 + \gamma_2 {C_D}^* - \gamma_3 (C_D^*)^2 - E_D^* + \alpha_4 (E_D^*)^2 \tag{41}$$

and combining like terms and simplifying yields

$$P_D = \left(\frac{(\alpha_2 - \alpha_1)}{\alpha_1 + \alpha_2}\right) Y_U + \left(\frac{\alpha_2 \alpha_1^2 - \gamma_1 \alpha_2^2}{(\alpha_1 + \alpha_2)^2}\right) Y_U^2 + \left(\frac{(\alpha_4 - \alpha_3)}{\alpha_3 + \alpha_4}\right) Y_D + \left(\frac{\alpha_4 \alpha_3^2 - \gamma_3 \alpha_4^2}{(\alpha_3 + \alpha_4)^2}\right) Y_D^2 \qquad (42)$$

Equation (42) requires the further restriction $\gamma_0 = 1$ and $\gamma_2 = 1$.

The estimated EKC model follows

$$P_D = \beta_0 + \beta_1 Y_U + \beta_2 Y_U^2 + \beta_3 Y_D + \beta_4 Y_D^2 \qquad (43)$$

where P_D is BOD per capita, Y_U is upstream income, Y_D is downstream income, and $\beta's$ are coefficients to be estimated.

Linking the theoretical model with the empirical model the second order marginal effects of consumption and effort on utility for the upstream country α_1 and α_2 and downstream country α_3 and α_4 can be derived from the following:

$$\left(\frac{(\alpha_2 - \alpha_1)}{\alpha_1 + \alpha_2}\right) = \beta_1 \qquad (44)$$

$$\left(\frac{\alpha_2 \alpha_1^2 - \gamma_1 \alpha_2^2}{(\alpha_1 + \alpha_2)^2}\right) = \beta_2 \qquad (45)$$

$$\left(\frac{(\alpha_4 - \alpha_3)}{\alpha_3 + \alpha_4}\right) = \beta_3 \qquad (46)$$

$$\left(\frac{\alpha_4 \alpha_3^2 - \gamma_3 \alpha_4^2}{(\alpha_3 + \alpha_4)^2}\right) = \beta_4 \qquad (47)$$

Solving for α_3 in terms of β_1, β_2, and γ_1 yields

$$\alpha_3 = \left(\frac{4\beta_4 + \gamma_3 (1 + \beta_3)^2}{(1 - \beta_3)^2}\right) \qquad (48)$$

The parameter γ_3 is unknown. To ensure concavity let $\gamma_3 = 0.5$. The parameter γ_3 can take any positive value as long as $\left(\frac{\delta U_D}{\delta C_D}\right) > 0$. Once α_3 is solved for, the following expression can solve for α_4:

$$\alpha_4 = \left(\frac{\alpha_3 (1 + \beta_3)}{1 - \beta_3}\right). \qquad (49)$$

The parameters α_1 and α_2 can be solved using β_1 and β_2 in a similar manner.

Although this model is somewhat restrictive, this appears to be the first attempt to link a theoretical model of an EKC with an empirical model. This is important because the underlying causes of an EKC are debated. Some EKC theorists believe citizens make “greener” consumption choices as they grow richer, while other theorists believe the EKC is a reflection of harsher environmental regulations in higher income countries. By using the EKC empirical results to derive underlying second order effects of consumption and effort on utility, this may offer some insight into how consumers value consumption and effort and where their income should be spent.

Data

The data for this paper consists of a panel of 6 member countries of the EU from 1980 to 2000. BOD levels are from Earth Trends (2010) and income per capita for countries come from Penn World Tables (2009). BOD levels are measured in a laboratory over a fixed time and temperature. Initial BOD levels are compared to a later sample and the difference represents the reported BOD level. This data is an updated version of data originally gathered by a World Bank study by Hettige, Mani, and Wheeler (1998). The BOD measures reported include only pollution from industrial activities and not from non-point sources including agricultural runoff. BOD levels are expressed in per capita terms.

Data scarcity is a major hurdle in EKC studies. Although several country level yearly data are available for BOD measures (ECONSTATS, EARTHTRENDS, etc.), data are often totally unavailable for many countries or available for only a few years. The six countries comprising this dataset have complete data for the years 1980-2000 to avoid an unbalanced dataset. Major rivers in the EU include the Danube and Rhine Rivers, both of which snake through many countries not included in this dataset. The absence of these countries from the dataset is because the river forms the border between two countries so that downstream dependence is not relevant. For example, the Danube River forms the entire length of the border between Romania and Moldova; these countries were omitted from the dataset. I assume that the major rivers will be polluted and the aggregate country BOD measures are representative of the actual BOD levels of the rivers in the study. For a list of upstream and downstream countries and common rivers, see Table 2.1.

From the United States Environmental Protection Agency (USEPA) webpage, BOD "measures the amount of oxygen consumed by microorganisms in decomposing organic matter in stream water." A result of high BOD levels is a reduction in oxygen for aquatic organisms. The loss in oxygen may cause some organisms to suffocate and die. BOD is a popular pollution indicator in water EKC studies because of data availability, common standard of measurement across different regions, and association with human activity (Sigman 2002). Furthermore, BOD is relevant in the present study because BOD has been found to travel downstream for great distances and up to 34% can travel from upstream to downstream countries (Sigman 2002). BOD levels decreased in European rivers in the 1990s but have recently been trending upwards (European Commission 2010).

Total BOD discharges are available from other websites but for considerably fewer years. An EKC relationship between GDP and pollution would occur within a country after several years of economic growth. Data from EarthTrends was chosen since this site has the longest time span for BOD data.

A problem that has been pointed out in previous EKC studies is the difficulty in discerning proper policy implications due to nonrobust results across studies. That is, any policy suggestion only holds for the countries included in a particular dataset and cannot be generalized to other countries. By focusing on EU countries I mitigate that problem because all EU countries have common economic and environmental policies so any policy recommendation would be relevant.

As defined by the European Commission (2010) webpage, sustainable development means "meeting the needs of present generations without jeopardizing the ability of futures generations to meet their own needs." The needs of future generations encompass economical, environmental, and social needs, all of which are interdependent with each other. Again, an inverted U-shaped EKC on downstream pollution with respect to upstream country's income would be evidence that it is possible to promote economic growth and decrease pollution levels.

Pooled Mean Group Estimation

Several methods have been taken in EKC studies to estimate dynamic panel models. Arellano-Bond GMM estimation (Halkos 2003) has been used in EKC studies. Typically, this method is used in panel studies where individual units, N, is larger than the time units, T. With panel data spanning many years and countries, Pesaran et al. (1999) propose the pooled mean group estimator. Although the number of countries is not large in this sample (N=6) the pooled mean group estimator is less restrictive than fixed effects panel estimation and is thus used in the present study. Pooled mean group estimation has been applied in EKC studies on sulfur emissions (Perman and Stern 2003) and more recently in carbon dioxide studies (Martinez-Zarzosa and Bengochea-Morancho 2004). Following Martinez-Zarzosa and Bengochea-Morancho (2004), the long run EKC empirical model is

$$BOD_{D_{i,t}} = \beta_{0_i} + \beta_{1i} Y_{U_{i,t}} + \beta_{2i} Y_{U_{i,t}}^2 + \beta_{3i} Y_{D_{i,t}} + \beta_{4i} Y_{D_{i,t}}^2 + \eta \tag{50}$$

Because estimating the above regression will yield spurious results with a panel including many years, Pesaran et al (1999) propose the pooled mean group estimator. The pooled mean group estimator is very similar to the single equation error correction model. Assuming income and its square are I(1), implying the error term η_{it} is I(0), the autoregressive distributive lag (ARDL) equation of (1) is

$$\Delta BOD_D = \gamma_i + \delta_{10i} Y_{U_{i,t}} + \delta_{11i} Y_{U_{i,t-1}} + \delta_{20i} Y_{U_{i,t}}^2 + \delta_{21i} Y_{U_{i,t-1}}^2 + \delta_{30i} Y_{D_{i,t}} + \delta_{31i} Y_{D_{i,t-1}} + \delta_{40i} Y_{D_{i,t}}^2 + \delta_{41i} Y_{D_{i,t-1}}^2 + \lambda_i BOD_{i,t-1} + \eta_{it}$$

where the regressors include lags of income and its square and the lag of BOD. The error correction model takes the form

$$\Delta BOD_D = \varphi\left(BOD_{D_{i,t-1}} - \beta_{0i} - \beta_{1i} Y_{U_{i,t}} - \beta_{2i} Y_{U_{i,t}}^2 - \beta_{3i} Y_{D_{i,t}} - \beta_{4i} Y_{D_{i,t}}^2\right) - \delta_{11i} \Delta Y_{U_{i,t-1}} - \delta_{21i} \Delta Y_{U_{i,t-1}}^2 - \delta_{31i} \Delta Y_{D_{i,t-1}} - \delta_{41i} \Delta Y^2{}_{D_{i,t-1}} - \lambda_i BOD_{D_{i,t-1}} + \eta_{it}$$

where

$$\beta_{0i} = \left(\frac{\gamma_i}{1-\lambda_i}\right), \beta_{1i} = \left(\frac{\delta_{10i}+\delta_{11i}}{1-\lambda_i}\right), \beta_{2i} = \left(\frac{\delta_{20i}+\delta_{21i}}{1-\lambda_i}\right), \beta_{3i} = \left(\frac{\delta_{30i}+\delta_{31i}}{1-\lambda_i}\right), \beta_{4i} = \left(\frac{\delta_{40i}+\delta_{41i}}{1-\lambda_i}\right), \varphi = -(1-\lambda_i).$$

The parameters $\beta_{0i}, \beta_{1i,}\beta_{3i},$ and β_{4i} represent the long run coefficients in equation (1) and are the coefficients from which parameters for consumption and environmental effort in upstream and downstream countries, $\alpha_1, \alpha_2, \alpha_3,$ and α_4 are derived. Pesaran et. al (1999) discuss three ways to estimate dynamic panels including the mean group (MG) approach, pooled mean group approach (PMG) and dynamic fixed effects estimator (DFE). PMG estimation restricts long run coefficients to be identical across countries and allows short run coefficients to vary. PMG estimation is used in the present study.

Results

The results in Table 2.2 indicate an EKC for the downstream BOD with respect to downstream income with a turning point of \$23,339 annual per capita income. The standard error of the turning point is derived through error propagation. Some of the countries in the dataset had surpassed this income level in 2000 while other countries were below the turning point. Table 2.1 includes downstream countries and per capita GDP in 2000. Downstream BOD appears to decrease with economic growth in the upstream country.

Results from PMG estimation are in Table 2.2. I derive the marginal effects of downstream consumption α_3 and effort α_4 on downstream utility, from the significant downstream coefficients β_3 and β_4. The derived results are in Table 2.3. I do not derive the marginal effects of upstream consumption α_1 and effort α_2 on downstream utility, because β_1 and β_2 are not both significant. Standard errors are derived with the delta method.

The derived parameters α_3 and α_4 are significant with values close to $\gamma_1 = 0.5$ and $\alpha_4 > \alpha_3$. First order conditions of downstream consumption and effort on downstream utility are $\left(\frac{\partial U_D}{\partial C_D}\right) = 1 - 2\alpha_3 C_D$ and $\left(\frac{\partial U_D}{\partial E_D}\right) = 1 - 2\alpha_4 E_D$. Although the data do not include values of consumption C and effort E, assuming $C_D > E_D$ and given α_3 and α_4 have values close to 0.5, $\left(\frac{\partial U_D}{\partial C_D}\right) \approx 1 - C_D$ and $\left(\frac{\partial U_D}{\partial E_D}\right) \approx 1 - E_D$ with $\left(\frac{\partial U_D}{\partial E_D}\right) > \left(\frac{\partial U_D}{\partial C_D}\right)$. This property result implies that utility is increasing more on the margin with respect to effort in α_4 than with respect to consumption in α_3. This may be expected as these countries reveal an EKC. Although similar, there are stronger diminishing returns to utility with respect to effort than with respect to consumption.

This paper assumes that the EKC is a result of a combination of more environmentally friendly consumption choices and environmental effort. Given this assumption, depending on the effect of consumption and effort on utility will determine where an extra dollar of income should be spent. Because the downstream countries reveal an EKC with consumption and effort both positively affecting utility with minor, nearly identical diminishing marginal effects, the conclusion is that consumers would divide an extra dollar of income between consumption and effort. It is incorrect to believe that the EKC is purely consumption-driven and money spent on effort is “wasted.”

Of course, these results should be interpreted with caution. Derived parameters may differ across datasets. In the presence of an EKC and large diminishing marginal effects of consumption on utility in α_3 relative to diminishing marginal effects of effort on utility in α_4, more income should be spent on effort. If $\alpha_4 > \alpha_3$, utility has smaller diminishing marginal effect with respect to consumption than effort. If an EKC is present it is most likely consumption-driven at the margin.

Conclusion

This paper investigates downstream dependence in an EKC for water pollution. The question this paper addresses is whether downstream pollution can be redressed with income growth in the upstream country. A theoretical model is developed that relates directly with the empirical EKC model to derive parameters for upstream and downstream consumption and effort.

There is evidence of an EKC in the downstream countries. For this particular dataset, economic growth in the upstream country decreases pollution downstream. Thus, it is beneficial to be downstream from a rich country and pro growth policies in the upstream country are important for the environment in the downstream country. Derived second order effects of consumption and effort on pollution reveal how upstream and downstream consumption choices and effort affect downstream utility. In particular, it appears there are diminishing, nearly identical, derived second order effects of consumption and effort on pollution, implying an extra $1 of income can be spent equally on consumption and effort without much of a difference on utility. This result is particularly important because many EKC theorists believe the EKC is a natural result of consumers making environmentally friendly consumption choices as they grow rich and environmental regulations may not be necessary. It is more likely, however, EKCs are driven by "greener" consumption choices and environmental regulations. As the results indicate utility of consumers is increasing in consumption and effort, it is wrong to believe that money spent of effort is wasted. Future EKC studies may benefit from employing the theoretical model proposed in this paper to help devise appropriate policy for various pollution indicators.

Table 2.1 List of Countries and Rivers

DOWNSTREAM COUNTRY	UPSTREAM COUNTRY	RIVER	Downstream Income per capita (expressed in year $2000)
Austria	Germany	Danube	27600
France	Switzerland	Rhine	24000
Netherlands	Germany	Rhine	28000
Portugal	Spain	Torne	16900
Luxembourg	France	Rhine	54100
Hungary	Germany	Danube	11300

Table 2.2 Pooled Mean Group Estimation

Variables	Coefficients
Long Run Coefficients	
Y_U	-7.84e-7** (4.20e-7)
Y_U^2	-3.14 (1.11e-11)
Y_D	1.84e-6*** (5.35e-7)
Y_D^2	-3.80e-11*** (1.30e-11)
Turning Point	$23,339*** (10,869.91)

std errors in parenthesis *10%, ** 5%, ***1% statistical significance

Table 2.3 Second Order Effects

Parameters	Derived Values
α_3	0.50000184*** (5.35e-07)
α_4	0.50000368*** (1.06e-06)

std errors in parenthesis *10%, ** 5%, ***1% statistical significance

Chapter 3 - Water Abundance and an EKC for Water Pollution

The Environmental Kuznet's Curve (EKC) posits an inverted U-shaped relationship between pollution and economic growth. This curve implies that as poor countries become richer any increasing pollution problems will be redressed. Since the initial study by Grossman and Krueger (1991), empirical EKC studies have become popular. Perhaps one reason for the continued relevance of EKC studies in the environmental economics literature is that there is no consensus on the existence of an EKC. Stern (2004) discusses several of the econometric problems associated with EKC studies that may explain inconsistent results across studies. One of the problems is omitted variable bias, as pollution reduction could be a result of factors other than an increase in per capita GDP as the EKC theory suggests (Stern 2004). The result of omitted variables may lead to overstated effects of income.

As Gassebner, Lamlay, and Sturmz (2011) explain, an EKC may exist for two reasons. Relating economic growth to the production side of the economy, Grossman and Krueger (1995) divide economic growth into three components: scale, technology, and composition effects. An economy grows with increased production inevitably causing more pollution. This is the scale effect. The technology effect describes an economy that moves to cleaner or "greener" technology as the country becomes rich. Lastly as a country goes from poor to rich, it may move from a heavy industrial sector to a more service oriented economy reducing pollution. If technology and composition effects are greater than scale effects, this may result in an EKC. This explanation for an EKC relates economic growth to changes in production. A second explanation for the existence of an EKC relates economic growth to changes in consumption patterns. As citizens become wealthier they begin to demand environmental quality (Antle and Heidebrink 1995).

As the EKC may be production or consumption driven, other explanatory variables typically follow within these two broad categories. On the production side, trade openness (Cole 2004, Copeland and Taylor 1994, Cole 2000), inward forward direct investment (Antweiler et. al 2001), real GDP growth (Carlsson and Lundström 2003) , industrial share of output and labor input (Neumayer 2003), and electricity production (Neumayer 2003) have been considered as possible determinants of pollution.

On the consumption side, additional explanatory variables include income inequality (Torras and Boyce 1998), economic freedom (Carlsson and Lundström 2003), political freedom (Carlsson and Lundström 2003), education levels (Klick 2002), urban population (Cole and Neumayer 2004), and population density (Borghesi 2006).

The purpose of the present paper is to determine the effect of water abundance on an EKC for water pollution. Consumers may be more protective of a scarce water supply as the marginal cost of water pollution would be higher than if water was abundant. The results of this paper confirm the importance of the inclusion of water abundance in EKC regressions for water pollution. Including water abundance in an EKC for water pollution eliminates the effect of income on pollution.

The rest of the paper is divided as follows. Section 2 provides a literature review of some of the determinants of pollution previously used in EKC studies. Section 3 discusses data. Estimation methods are described in Section 4. Section 5 discusses results.

Literature Review

Perhaps the most common explanatory variable in EKC studies is trade openness. Trade openness or intensity is the ratio of imports and exports over GDP (Gassebner et al. 2010). The inclusion of openness in EKC studies is to test for the pollution haven hypothesis which says that polluting industries will relocate from developed to developing nations that tend to have fewer environmental regulations. This variable is included in both air pollution (Cole and Neumayer 2004; Cole 2004) and water pollution studies (Cole and Neumayer2004; Cole 2004) with mixed findings (Cole and Neumayer 2004). Cole (2004) includes trade intensity, share of dirty imports from non-OECD countries in total imports and share of dirty exports to non-OECD countries in total exports. Cole also includes a cubic term for income, which is commonly employed in studies to determine whether at very high income levels pollution levels rise. Data includes ten air and water pollution indicators on a sample of OECD countries from 1980-1997. Fixed effects estimation results for most pollution indicators show an inverted U-shaped EKC exists for the panel of countries; an increase in trade intensity lowers pollution and manufacturing has a positive effect on pollution.

Lee et. al (2010) include trade openness, population density, and a lagged dependent variable in their water pollution EKC study on a panel of 97 countries using annual BOD data from 1980-2001. Using GMM estimation, they do not find an EKC for the entire panel but then find evidence of EKC's for Europe and America once breaking the panel of countries into regions. Turning points for America and Europe are $13,956 annual per capita income and $38,221 annual per capita income in 2000 US dollars. Trade openness and population density are not found to be statistically significant in the full panel or the regional panels.

Popular demand-driven explanatory variables include population density and policy variables. Panayatou (1997) includes population density, policy variables, and real GDP growth as explanatory variables in an EKC study of sulfur dioxide emissions using an unbalanced panel of 30 countries from 1982-1994. Results indicate that population density and GDP growth do lead to a higher turning point; however, policy variables have a larger negative effect on the turning point of the EKC implying effective regulation is good for the environment. Lin and Lisgow (2011) find political variables and civil liberties matter for five of eleven water pollutants.

Iwata, Okata, and Samreth (2011) investigate the role of nuclear energy in an EKC for carbon dioxide in France. The inclusion of nuclear energy as an explanatory variable accounts for the production of energy. Following Ang (2007) and Jalil and Mahmut (2009) the authors also include energy consumption and trade openness as explanatory variables. Yearly data runs from 1960 to 2003. Using the autoregressive distributive lag (ARDL) approach developed by Pesaran (1999) they find evidence of an EKC for France and that nuclear energy can reduce CO_2 emissions.

The effect of urbanization on CO_2 is investigated by Shahbaz, Jalil, and Dube (2010) in an EKC time series study for Portugal. They also control for trade openness and energy consumption, both of which are found to positively affect CO_2 emissions.

In perhaps the most thorough discussion of pollution determinants to date, Gassebner,Lamlay, and Sturmz (2011) employ Extreme Bound Analysis to test the robustness of nineteen different explanatory variables in an EKC for water and air pollution. BOD is the water pollution indicator and CO_2 is the air pollution indicator. Of the 19 explanatory variables the authors only find two variables, industry share, as measured by employment, and income inequality, to be robust to model specification. These results question the validity of model specifications used in previous studies and suggests future studies should include checks on the robustness of their results. The authors find an EKC with respect to water pollution with a turning point of $26,500 annual per capita income (in 1995 dollars) and do not find an EKC for air pollution.

Data

Yearly data covers 36 developed and developing countries from 1980-2000. The water pollution indicator for this paper is biochemical oxygen demand (BOD) from the source EarthTrends (2007). This webpage defines BOD as “the amount of oxygen that bacteria in water will consume in breaking down waste.” The site goes on to explain that the more oxygen used to break down waste the less oxygen there is available for aquatic life so that a polluted river will have a high level of BOD. BOD is measured in kilograms per day. The measure is multiplied by 365 (to get yearly BOD estimates) and then divided by population (to get BOD per capita). Population data is from Penn World Tables (2009).

One drawback of this data is that BOD levels are from industrial waste only, and do not include nonpoint sources of pollution such as agricultural runoff that could contribute to water pollution. Despite this drawback, EarthTrends (2007) contends that the data “are fairly reliable because sampling techniques for measuring water pollution are more widely understood and much less expensive than those for air pollution.” This indicator is common in water pollution EKC studies due to data availability.

Income per capita comes from the Penn World Tables (2009). Water abundance data is constructed from yearly statistics found in EarthTrends (2007) and Penn World Tables (2009). First, the total water availability measured in cubic kilometers is collected for every country in the dataset. This amount stays constant over time. Water availability is then divided by population data from Penn World Tables to convert water availability to per capita terms. Thus, as population increases over time (in most countries), water availability decreases. Water availability varies widely across countries in the dataset. Groups of water-scarce and water-abundant countries are included in Figure 4.1 and Figure 4.2, respectively, to get an idea of how water abundance varies across countries.

Estimation Methods

Panel estimation techniques like fixed effects (FE) are typical in EKC studies. A shortcoming of FE estimation is that slope coefficients are restricted to be the same across countries, which may be an unrealistic assumption.

Recently, more flexible estimation techniques that allow for slope heterogeneity across countries have been used in EKC studies. These techniques include mean group (MG) estimation proposed by Pesaran and Smith (1995) and pooled mean group (PMG) proposed by Pesaran, Shin, and Smith (1999). PMG estimation is particularly useful in empirical studies with panels covering many years and many countries (MartÍnez-Zarzosa and Bengochea-Morancho 2004).

MartÍnez-Zarzosa and Bengochea-Morancho (2004) apply PMG, MG, and dynamic fixed effects (DFE) estimation to an EKC study for CO_2 on a panel of 22 OECD countries using data from 1975 to 1998 and find, with a cubic EKC specification, an N-shaped relationship between CO_2 levels and income.

Iwata, Okada, and Samreth (2011) estimate an EKC study for CO_2 using PMG, MG, and DFE estimation. They also test for the effects of nuclear energy production in their paper. Hausman tests reject MG estimation in favor of PMG estimation. Results support an EKC for the full sample, but the turning point is high enough that CO_2 is increasing monotonically within the observed range of income. Nuclear energy production has a negative effect on CO_2 emissions.

Bella, Massidda, and Etzo (2010) compare results from PMG, MG, FE, random effects (RE), and random coefficients (RC) estimation for an EKC for CO_2. They include electric power consumption as an additional explanatory variable as well as test for a cubic specification for an EKC. The data consists of 77 countries from 1971-2006. Energy consumption is found to positively affect the pollution in most specifications. Evidence of an EKC is found for the full sample but not when data is divided into OECD countries and non-OECD countries.

Following these papers, I estimate an EKC regression using PMG estimation to see how water abundance affects an EKC for water pollution. PMG estimation is less restrictive than more common panel estimation methods. PMG allows slope heterogeneity in the short run and long run coefficients are constrained to be equal across countries. As in chapter 2, BOD is initially regressed on population and the residual from this regression is the dependent variable in the following PMG estimation. Results controlling for population in this manner were compared to a regression where BOD is expressed in per capita terms. Akaike information criteria (AIC) prefer the EKC model specification presented in this chapter. Alternative methods for controlling for population are discussed further in chapter 4. The long run EKC relationship in the present paper is

$$BOD_{it} = \beta_{0i} + \beta_{1i}Y_{it} + \beta_{2i}Y_{it}^2 + \beta_{3i}W_{it} + \beta_{4i}W_{it}^2 + \beta_{5i}Y_{it}W_{it} + \beta_{6i}(Y_{it}W_{it})^2 \qquad (1)$$

where BOD_{it} is biochemical oxygen demand, β_{0i} represents country fixed effects, Y_{it} is per capita GDP, W_{it} is water abundance, interaction terms between water abundance and per capita income, $Y_{it}W_{it}$, as well as its square are included to allow flexibility in the EKC curve and calculation of turning points. Coefficients to be estimated are represented by β's, and i and t are country and year subscripts. All variables are in natural logarithms.

Following Martínez-Zarzosa and Bengochea-Morancho (2004), the PMG estimator assumes variables are I(1) and cointegrated within countries. The autoregressive distributive lag ARDL (1,1,1,1) equation includes one period lags of explanatory variables as well as a lagged dependent variable in the following expression

$$BOD_{it} = \gamma_i + \delta_{10i}Y_{it} + \delta_{11i}Y_{i,t-1} + \delta_{20i}Y_{i,t}^2 + \delta_{21i}Y_{i,t-1}^2 + \delta_{30i}W_{i,t} +$$

$$\delta_{31i}W_{i,t-1} + \delta_{40i}W_{i,t}^2 + \delta_{41i}W_{i,t-1}^2 + \delta_{50i}Y_{i,t}W_{i,t} + \delta_{51i}(YW)_{i,t-1} + \delta_{60i}(Y_{it}W_{it})^2 +$$

$$\delta_{61i}(YW)_{i,t-1}^2 + \delta_{70i}BOD_{i,t-1} + \mu_{it} \qquad (2)$$

$$i = 1,..,38 \quad t = 1,\dots,21.$$

The error correction model combines the long run EKC relationship from (1) with the short run ARDL model (2) in the following equation

$$\Delta BOD_{it} = \varphi\big(BOD_{i,t-1} - \beta_{0i} - \beta_{1i}Y_{it} - \beta_{2i}Y_{i,t}^2 - \beta_{3i}W_{i,t} - \beta_{4i}W_{i,t}^2 -$$

$$\beta_{5i}(Y_{i,t}W_{i,t}) - \beta_{6i}(YW)_{i,t}^2\big) - \delta_{11i}\Delta Y_{i,t-1} - \delta_{21i}Y_{i,t-1}^2 - \delta_{31i}W_{i,t-1} - \delta_{41i}W_{i,t-1}^2 -$$

$$\delta_{51i}YW_{i,t-1} - \delta_{61i}(YW)^2{}_{i,t-1} + \eta_{it} \qquad (3)$$

where

$\beta_{0i} = ((\gamma_i)/(-\varphi_i))$, $\beta_{1i} = \left(\frac{\delta_{10i}+\delta_{11i}}{-\varphi_i}\right)$, $\beta_{2i} = \left(\frac{\delta_{20i}+\delta_{21i}}{\varphi_i}\right)$, $\beta_{3i} = \left(\frac{\delta_{30i}+\delta_{31i}}{-\varphi_i}\right)$, $\beta_{4i} = \left(\frac{\delta_{40i}+\delta_{41i}}{-\varphi_i}\right)$,

$\beta_{5i} = \left(\frac{\delta_{50i}+\delta_{51i}}{-\varphi_i}\right)$, $\beta_{6i} = \left(\frac{\delta_{60i}+\delta_{61i}}{-\varphi_i}\right)$.

The error corrected coefficients (in parenthesis) represents long run coefficients that are pooled and constrained to be equal across countries. The differenced coefficients represent short run coefficients and are allowed to vary across countries.

Before PMG estimation, the Im, Pesaran, Shin (2003) panel unit root test tests variables for a unit root because PMG estimation requires variables to be I(1).The Im, Pesaran, Shin (IPS) panel unit root test is based on the Dickey-Fuller unit root tests applied in time series studies.

Following Enders (2004) to perform the IPS test, the following augmented Dickey-Fuller (ADF) regression is applied to each cross sectional unit

$$\Delta x_{it} = \alpha_{i0} + \theta_i x_{i,t-1} + \alpha_{i2} t + \Sigma_{j=1}^{p_i} \beta_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \text{ where } i = 1, \ldots., N \text{ and}$$

$t = 1, \ldots, T$

where x is the vector of variables (BOD, Y, W), p_i are different lag lengths, t is a time trend, and $\alpha_{i0}, \theta_i, \alpha_{i2}, \beta_{ij}$ are coefficients to be estimated. The null hypothesis of a unit root for each individual time series is $\theta_i = \alpha_{i2} = \beta_{ij} = 0$ so that $\Delta x_{it} = \varepsilon_{it}$. The t-statistic for the IPS panel unit root test t^* takes the individual t-statistic for each series t_i and forms the sample mean in the following equation, $t^* = (\frac{1}{n})\Sigma_{i=1}^{n} t_i$. Results from the panel unit root test reported in Table 3.1 indicate all variables are I(1).

To test the long run relationship between the variables the panel cointegration test developed by Westerlund (2007) is implemented. Many popular cointegration tests such as the Pedroni (2004) test for panel data or Engle Granger test for time series data are residual based. A shortcoming of residual based cointegration tests are that long run error cointegration and short run dynamics are constrained to be equal (Westerlund 2007), referred to as the common factor restriction (Kremers, Ericsson, and Dolado 1992). This new panel cointegration technique is structural rather than residual based and does not have a common factor restriction. The Westerlund panel cointegration test calculates four test statistics: G_t, G_a, P_t, and P_a. G_t and G_a are group mean statistics and P_t and P_a are panel statistics. The group mean statistics have a null hypothesis of no cointegration for all countries against the alternative of cointegration for at least one series. The panel statistics have a null hypothesis of no cointegration for all countries against the alternative of cointegration for the entire panel. Results reported in Table 3.2 indicate the null of no cointegration can be rejected in the G_t statistic, evidence of cointegration for some series. Proceeding with PMG estimation, the following basic EKC model is estimated

$$BOD_{it} = \beta_{0i} + \beta_{1i}Y_{it} + \beta_{2i}Y_{it}^2 \tag{4}$$

to compare with the full model that includes water abundance terms. Turning points are calculated for each regression. The turning point is the level of income at which pollution degradation is maximized. The turning point for basic model can be calculated as $\tau_1 = \exp\left(\frac{\beta_{1i}}{-\beta_{2i}}\right)$ and the turning point for the full model is $\tau_2 = \exp\left(\frac{\beta_{1i}+\beta_{5i}W^*}{-2(\beta_{2i}+\beta_{6i}W^*)}\right)$ where W^* is the mean water abundance for the data subset.

Results

Results are in Table 3.3 from the PMG estimation. Coefficient estimates are long run parameters. The results suggest sensitivity of the EKC to the inclusion of water abundance. The turning point in the basic model is \$2631 annual per capita income. Because the models are estimated in natural logarithms, the value and standard error of $\left(\frac{\beta_{1i}}{-\beta_{2i}}\right)$ and $\left(\frac{\beta_{1i}+\beta_{5i}W^*}{-2(\beta_{2i}+\beta_{6i}W^*)}\right)$ are included in Table 3.3 (in the row that begins "Value of X"). Statistical significance of these expressions would indicate statistically significant turning points, $\tau_1 = \exp\left(\frac{\beta_{1i}}{-\beta_{2i}}\right)$ and $\tau_2 = \exp\left(\frac{\beta_{1i}+\beta_{5i}W^*}{-2(\beta_{2i}+\beta_{6i}W^*)}\right)$. Including water abundance completely eliminates the EKC. In fact, neither income per capita nor its square are statistically significant, but water abundance and its square are both statistically significant. As the coefficient on water abundance is negative and the coefficient on the square of water abundance is positive, the relationship between BOD and water abundance is u-shaped. This result suggests at low levels of water abundance perhaps the marginal cost of polluting the water source is very high, and citizens take great care not to dirty the water supply, resulting in the negative coefficient on water abundance. However, at high levels of water abundance the marginal cost of pollution is low and pollution increases, resulting in the positive coefficient on the square of water abundance. The calculated turning point for water abundance describes the abundance level at which pollution begins to increase. The turning point for water abundance is 373 cubic kilometers per person per year. Three water-scarce countries included in the dataset were below this turning point in the year 2000, including Singapore (148 km^3), Jordan (187 km^3) and Israel (291 km^3). All other countries included in this dataset were above this turning point.

Conclusion

This paper explores the literature on determinants of pollution previously used in EKC studies. An overlooked yet relevant explanatory variable, water abundance, is included in an EKC regression for water pollution. The regression analysis is conducted on a full sample of 36 countries from with annual data from 1980-2000.

The results indicate that water abundance is a very important variable to include in water EKC studies. Its inclusion eliminates any evidence of an EKC and instead water abundance coefficients are found to be statistically significant. There appears to be a u-shaped relationship between water pollution and water abundance so that at low level of water pollution is decreasing but at high levels of water abundance pollution increases. This result is possibly due to marginal costs of pollution being high when water levels are low and marginal costs of polluting water is low when there is an abundant water supply.

This result offers an avenue for further research on the affect of resource abundance on pollution. While it wouldn’t be possible for air pollution studies (since air is abundant), other EKC papers that look at, for example, economic growth and deforestation, could be misspecified if they have not accounted for acres of wooded area.

Table 3.1 Panel unit root tests

Unit Root Test	*BOD*	*GDP*	*Abundance*
Level			
IPS test	-1.29	-1.34	-1.13
P-value	0.93	0.87	0.99
First Difference			
IPS test	-3.01	-3.00	-2.40
P-value	0.00	0.00	0.00

Table 3.2 Panel Cointegration

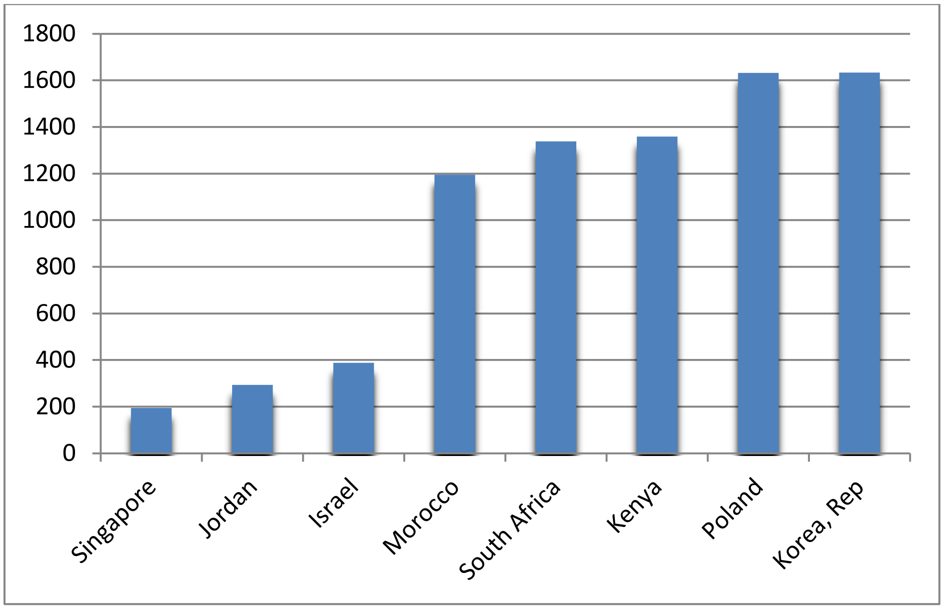
Statistic	Value	Z-value	P-value
Gt	-1.74	-2.07	0.02
Ga	-4.41	1.56	0.94
Pt	-4.52	0.83	0.80
Pa	-1.74	0.93	0.82

Table 3.3 Results

Variable	Without Water (Model 1)	With Water (Model 2)
Y	1.26*** (0.24)	0.72 (1.78)
Y^2	-0.08*** (0.02)	-0.06 (0.05)
W		-5.33** (2.61)
W^2		0.45*** (0.11)
YW		0.06 (0.22)
$(YW)^2$		-2.18e-5 (7.45e-4)
Turning Point	$2631	373 km^3
Value of X: Turning point=exp$^{(X)}$	7.88*** (2.48)	5.92* (3.24)
N	36	36

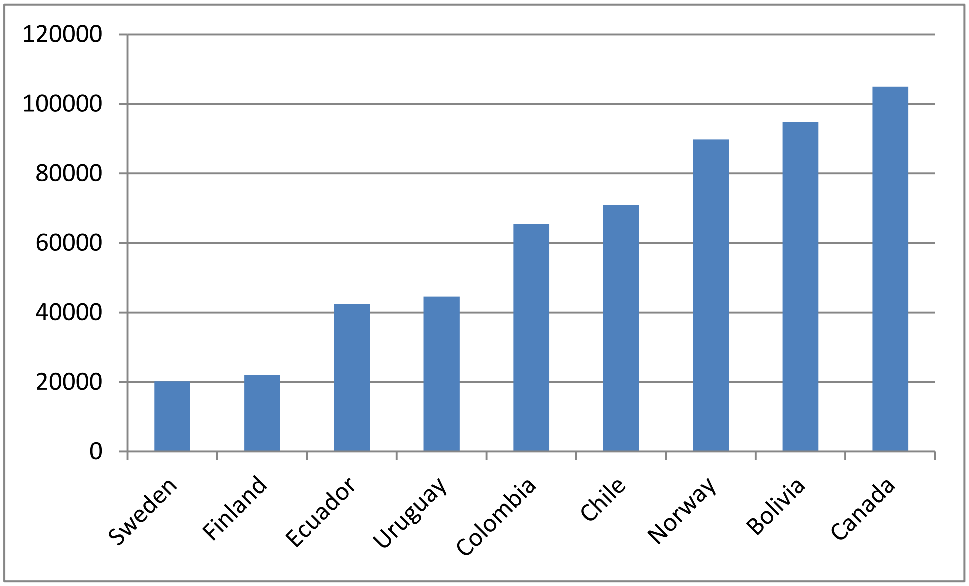
std errors in parenthesis *10%, ** 5%, ***1% statistical significance

Figure 3.1 Water Scarce Countries



Water abundance measured in km^3 per person per year

Figure 3.2 Water Abundant Countries



Water abundance measured in km^3 per person per year

Chapter 4 - Accounting for Population in an EKC for Water Pollution

This paper takes a look at the role of population in an EKC model. The data concerns water pollution, but the role of population in an empirical EKC model can be extended to various pollutants. The majority of EKC empirical studies utilize panel data (Panayatou 1997; Iwata, Okata, and Samreth 2011). In air pollution studies and water pollution studies, pollution indicators are measured either in total emissions (Panayotou 1993, Cole et. al 1997; Seldon and Song 1994; List and Gallet 1999; Stern and Common 2001) or concentrations (Panayotou 1997; Kaufmann et. al 1997). If measured in total emissions, air and water pollution indicators are usually expressed in per capita terms (Trabelesi 2012; Stern 2004). In EKC studies where the pollution is measured in concentrations, population density is sometimes included as an explanatory variable (Hwang 2007; Lee et. all 2010).

This paper does not argue the merits between pollution expressed in total emissions compared to concentration. For a discussion, various published critiques of the EKC are available (Stern 2004, Dasgupta et. al 2002). This paper focuses on the studies that express pollution in per capita terms, and offers an alternative method for controlling for population that could be useful in future studies.

Because the majority of EKC studies employ panel data analysis, it is important to control for population across countries. Higher populated experience more pollution in total. However, higher population does not necessarily lead to higher pollution per capita. If population increases faster than pollution, increases in population will be associated with lower pollution per capita. Theoretically, the EKC describes the relationship between economic growth and pollution, not economic growth and pollution per capita. Therefore, this paper seeks to reconcile the empirical desire to control for population across panel EKC studies with the theoretical model describing the relationship between pollution and economic growth.

This paper introduces a new way to control for population in EKC studies. Two models are estimated, each of which control for population in different a manner. Estimates are then compared across models. In Model 1, the water pollution indicator BOD is measured in kilograms per day per person. This method is typical in EKC studies. In Model 2, the new method for controlling for population, BOD (measured in kilograms per day) is regressed on population, $P = \mu_0 + \mu_1 Pop + \varepsilon$. The residual from this regression, ε, represents the pollution not explained by population. This residual is then used as the dependent variable BOD in the EKC regression. By Method 2, it is possible to control for population differences across countries in the first step while depicting the EKC relationship between pollution and economic growth in the second step.

The results reveal that estimates and EKC turning points vary greatly depending on how population enters into the EKC model. The Akaike Information Criteria (AIC) indicates which model is preferred and results show that Model 2 is preferred to Model 1. This suggests empirical EKC studies should consider other ways to control for population.

Data

The dataset is identical to the dataset in Chapter 3. The dataset includes a balanced panel of 37 countries from 1980 to 2000. BOD data comes from EarthTrends (2007). BOD measures the amount of oxygen required to break down bacteria by organisms. A higher BOD level is equivalent to higher pollution. Income per capita and population data are from Penn World Tables (2009). All variables are in natural logarithms.

Methods

As in the previous two chapters, pooled mean group (PMG) estimation is employed in this chapter. Unlike the more traditional fixed effects model, the PMG estimator is more flexible allowing short run coefficients to vary across countries and constraining long run coefficients to be the same. This method has been employed only recently in EKC studies (MartÍnez-Zarzosa and Bengochea-Morancho 2004; Iwata, Okada, and Samreth 2011; Bella, Massidda, and Etzo 2010).

The long run EKC model is

$$BOD_{it} = \beta_{0i} + \beta_{1i}Y_{it} + \beta_{2i}Y_{it}^{2}. \tag{1}$$

Following Martínez-Zarzosa and Bengochea-Morancho (2004), the autoregressive distributive lag model (ARDL) follows

$$\begin{gathered} BOD_{it} = \gamma_i + \delta_{10i}Y_{it} + \delta_{11i}Y_{i,t-1} + \delta_{20i}Y_{i,t}^{2} + \delta_{21i}Y_{i,t-1}^{2} + \delta_{30i}BOD_{i,t-1} \\ i = 1,..,38 \quad t = 1,\ldots,21. \end{gathered} \tag{2}$$

It is assumed variables are I(1) and cointegrated within countries. A one period lagged explanatory variable is included in the model.

PMG estimation combines the long run EKC relationship from (1) with the short run ARDL model (2) in the following equation

$$\begin{gathered} \Delta BOD_{it} = \varphi\left(BOD_{i,t-1} - \beta_{0i} - \beta_{1i}Y_{it} - \beta_{2i}Y_{i,t}^{2}\right) - \delta_{11i}\Delta Y_{i,t-1} \\ -\delta_{21i}Y_{i,t-1}^{2} + \eta_{it} \end{gathered} \tag{3}$$

where $\beta_{0i} = ((\gamma_i)/(-\varphi_i))$, $\beta_{1i} = \left(\frac{\delta_{10i}+\delta_{11i}}{-\varphi_i}\right)$, $\beta_{2i} = \left(\frac{\delta_{20i}+\delta_{21i}}{\varphi_i}\right)$. The error corrected coefficients (in parenthesis) represent long run coefficients that are pooled and constrained to be equal across countries. The differenced coefficients represent short run coefficients and are allowed to vary across countries.

Before PMG estimation, the Im, Pesaran, Shin (2003) panel unit root test tests variables for a unit root because PMG estimation requires variables to be I(1).The Im, Pesaran, Shin (IPS)panel unit root test is based on the Dickey-Fuller unit root tests applied in time series studies. Following Enders (2004), to perform the IPS test, the following augmented Dickey-Fuller (ADF) regression is applied to each cross sectional unit

$$\Delta x_{it} = \alpha_{i0} + \theta_i x_{i,t-1} + \alpha_{i2} t + \Sigma_{j=1}^{p_i} \beta_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \text{ where } i = 1, \ldots., N \text{ and}$$

$$t = 1, \ldots, T$$

where x is the vector of variables (BOD, Y, W), p_i are different lag lengths, t is a time trend, and $\alpha_{i0}, \theta_i, \alpha_{i2}, \beta_{ij}$ are coefficients to be estimated. The null hypothesis of a unit root for each individual time series is $\theta_i = \alpha_{i2} = \beta_{ij} = 0$ so that $\Delta x_{it} = \varepsilon_{it}$. The t-statistic for the IPS panel unit root test t^* takes the individual t-statistic for each series t_i and forms the sample mean in the following equation, $t^* = (\frac{1}{n})\Sigma_{i=1}^{n} t_i$. Results from the panel unit root test reported in Table 4.1 indicate all variables are I(1).

To test the long run relationship between the variables, the panel cointegration test developed by Westerlund (2007) is implemented. Many popular cointegration tests such as the Pedroni (2004) test for panel data or the Engle Granger test for time series data are residual based. A shortcoming of residual based cointegration tests are that long run error cointegration and short run dynamics are constrained to be equal (Westerlund 2007) referred to as the common factor restriction (Kremers, Ericsson, and Dolado 1992).

The Westerlund panel cointegration technique is structural rather than residual based and does not have a common factor restriction. The Westerlund test calculates four test statistics: G_t, G_a, P_t, and P_a. The first two are group mean statistics the second two are panel statistics. The group mean statistics have a null hypothesis of no cointegration for all countries against the alternative of cointegration for at least one series. The panel statistics have a null hypothesis of no cointegration for all countries against the alternative of cointegration for the entire panel. Results reported in Table 4.2 indicate the null of no cointegration can be rejected in the G_t statistic, evidence of cointegration for some series.

Results

Results from the two models are in Table 4.3. Results indicate that the manner in which population is controlled for greatly affects the EKC turning point. From two EKC models, the AIC criterion determines which is preferred. The first model is

$$BODPC = \alpha_0 + \alpha_1 Y + \alpha_2 Y^2$$

where $BODPC$ is biochemical oxygen demand per capita, Y is income per capita, and α's are estimated coefficients. Model 2 includes the OLS regression

$$BOD = \delta_0 + \delta_1 Pop + \varepsilon$$

where BOD is biochemical oxygen demand expressed in cubic kilometers per day, Pop is the yearly population estimates for given countries, δ's represent coefficients to be estimated, and ε is the error term. The error term represents the pollution not explained population.

The residual enters the following second stage regression,

$$\hat{\varepsilon} = \gamma_0 + \gamma_1 Y + \gamma_2 Y^2$$

where γ's are coefficients to be estimated. All variables are expressed in natural logarithms in both models. In the presence of an EKC we should expect a positive α_1 and a negative α_2 in model 1. In model 2, an EKC would be indicated by a positive γ_1 and a negative γ_2.

Turning points are

$$\tau_1 = \exp\left(\frac{\alpha_1}{-(2\alpha_2)}\right)$$

in model 1 and

$$\tau_2 = \exp\left(\frac{\gamma_1}{-(2\gamma_2)}\right)$$

in model 2.

Results suggest an EKC for the panel of countries with a turning point of $1,408 annual per capita income in model 1 and $2,631 annual per capita income in model 2.

The Akaike Information Criterion (AIC) determines which of the two models is preferred. The AIC is based on the log likelihood and follows AIC = -2ln(L) + 2q where q is the number of parameters and L is the log likelihood. The lowest AIC is the preferred model. The results for AIC are reported in Table 4.4 and show that Model 2 is preferred to Model 1.

Because the models are estimated in natural logarithms, the value and standard error of $(\frac{\alpha_1}{-(2\alpha_2)})$ and $(\frac{\gamma_1}{-(2*\gamma_2)})$ are included in Table 4.3 (in the column that begins “Value of X”). Statistical significance of these expressions would indicate statistically significant turning points in $\tau_1 = \exp\left(\frac{\alpha_1}{-(2*\alpha_2)}\right)$ and $\tau_2 = \exp\left(\frac{\gamma_1}{-(2\gamma_2)}\right)$. The values $X_1 = (\frac{\alpha_1}{-(2\alpha_2)})$ and $X_2 = (\frac{\gamma_1}{-(2\gamma_2)})$ appear to be significant indicating the turning points are statistically significant. 95% Confidence intervals, $C.I. = X_i \pm (1.96 * standard\ error\ X_i)$ for $X_i\ \ i = 1{,}2$, are constructed for both models we cannot reject that the turning points are equal to each other as the confidence intervals overlap. Confidence intervals are reported in Table 4.3.

Conclusion

This paper points out the care required in EKC studies to control for population. The majority of EKC studies control for population by expressing the pollution indicator in per capita terms. While controlling for population may be necessary, it may not be theoretically consistent. While more populated countries may pollute more, this does not necessarily translate into higher pollution per capita if population is growing faster than pollution.

Two models are estimated, each controlling for population differently. One model includes BOD in per capita terms and the other model employs a two stage regression where population is initially controlled before the EKC model is estimated. Results indicate EKCs for both models but with very different turning points. The turning point in the two stage model is nearly twice as large as the turning point in the per capita model, $2631 annual per capita income compared to $1408 annual per capita income.

Despite both turning points being relatively low, the GDP per capita of three countries including India, Kenya and Senegal fall between these two turning points for the year 2000 (the last year in the dataset). None of the countries' GDP per capita is below $1,408 annual per capita income in the year 2000. Therefore, if the per capita model was chosen over the two stage model, one would conclude all countries are past the turning point and are experiencing decreasing pollution with economic growth, when India, Kenya, and Senegal would still be facing increasing pollution with economic growth. Although the turning points are not significantly different from each other, the AIC criterion indicates the two stage model is preferred to a BOD per capita model. Future EKC studies may benefit by being wary of how population enters their models, as the present paper indicates the differences in results that may occur.

Table 4.1 Panel unit root tests

Unit Root Test	*BOD*	*GDP*
Level		
IPS test	-1.27	-1.17
P-value	0.95	0.99
First Difference		
IPS test	-4.35	-3.73
P-value	0.00	0.00

Table 4.2 Panel Cointegration

Statistic	Value	Z-value	P-value
Gt	-1.71	-1.89	0.03
Ga	-4.26	1.72	0.96
Pt	-4.63	0.75	0.77
Pa	-1.74	0.93	0.83

Table 4.3 Controlling for Population Model 1 vs. Model 2

MODEL	Y	Y_2	Turning Point	AIC	Log Likelihood	Value of X: Turning point=exp$^{(X)}$	Confidence Intervals (LL,UL)
MODEL 1	0.87*** (0.25)	-0.06*** (0.02)	$1382.44	-2181.97	1096.99	7.25*** (3.19)	(1.00,13.50)
MODEL 2	1.26*** (0.24)	-0.08*** (0.02)	$3135.97	-2184.51	1098.26	7.88*** (2.48)	(3.02,12.73)

Chapter 5 - Discussion of Three Essays on Environmental Kuznets Curve for Water Pollution

This dissertation consists of three essays on an EKC for water pollution. The EKC describes the relationship between pollution and economic growth as an inverted u-shaped curve. Economic growth naturally increases pollution levels, but as economic growth continues, at some point pollution levels lessen. In empirical EKC studies economic growth is typically measured by income per capita and various pollution indicators have been studied including carbon dioxide, and biochemical oxygen demand in water pollution EKC studies. The level of income per capita that maximizes pollution degradation is called the turning point.

A number of theories have been discussed as to why economic growth may eventually redress pollution problems. According to some economists, consumers begin demanding a cleaner environment once a certain level of sustainable income is reached. On the production side, as a country develops economic activities go from being manufacturing oriented to more service oriented activities. The production of services is relatively less polluting than producing manufactured goods which may help explain the inverted u-shaped EKC.

The water pollution indicator used in the dissertation is BOD, which is the most commonly used water pollution indicator due to data availability. The most basic EKC regression model takes the form, $E = \beta_0 + \beta_1 Y + \beta_2 Y^2$ where E is the pollution indicator, Y is income per capita, and β's are estimated coefficients.

Despite the extensive literature published on the EKC in the last 20 years, there are some holes in the literature, particularly in water EKC studies, that this dissertation is intended to fill. The second chapter, Downstream Dumping, looks at downstream dependence in an EKC for water pollution for a panel of European countries. Can economic growth in the upstream country help alleviate downstream water pollution or does it merely contribute to the problem? This question is answered by including upstream income per capita and its square as explanatory variables along with downstream income per capita and its square. The dependent variable is per capita BOD measured in kilograms per day. The BOD variable is a country average and the paper assumes this BOD level represents the BOD level in the shared river.

The data includes a panel of six EU member countries. EU member countries were chosen for the dataset because if upstream countries pollute countries then there is the possibility for the need for government intervention. Because EU member countries have common laws, the EU governing body could realistically tax upstream countries if they increased downstream pollution levels.

For this particular dataset, downstream BOD levels decline as upstream income rises. This result implies it is environmentally beneficial to be downstream from a rich country, and can be viewed as an argument in favor of the EU which generally promotes trade and other pro growth policies between members. With respect to downstream income and BOD levels, there is evidence of an EKC for water pollution with a turning point of $24,211 annual per capita income expressed in 2005 dollars. At this level of income four of the six European countries included in the dataset were pass the turning point.

In addition to these empirical results, a theoretical model is linked to the empirical EKC model. In the theoretical model, there are upstream and downstream agents whose utility are functions of consumption and pollution. Agents can spend their income on consumption and environmental effort. Using the estimated coefficients from the empirical model, one can derive parameters for consumption and effort for the upstream and downstream countries. These derived parameters represent second order effects of consumption and effort (of upstream and downstream agents) on downstream utility. The derived parameters between upstream and downstream countries can be compared to each other to devise appropriate policy. This theoretical model may be useful in future EKC studies.

Chapter 3, Water Abundance in an EKC for Water Pollution, considers the effect of water abundance on an EKC for water pollution. Water abundance is a widely overlooked variable that may affect the presence of an EKC or the turning point of an EKC. Data consists of a panel of 37 countries. Water abundance is measured in cubic kilometers per person per year. The square of water abundance is included. The hypothesis is that at low water levels the marginal cost of pollution is high so that the coefficient on water abundance will be negative. As water abundance increases, the marginal cost of pollution decreases so that the coefficient on the square of water abundance will be positive. Therefore the relationship between pollution and water abundance will be u-shaped. Interaction terms between income per capita and water abundance are included in the analysis. The hypothesis about water abundance cannot be rejected; there is a u-shaped relationship between pollution and water abundance. The effect of water abundance on pollution is strong; the inclusion of water abundance in the empirical model completely eliminates the effect that income has on pollution. In preliminary estimation that does not include water abundance, there is evidence of an EKC.

The fourth chapter discusses two approaches to controlling for population in an EKC for water pollution. The majority of EKC studies use panel data, and since population differs across countries typically the pollution indicator is expressed in per capita terms to control for population. A more populated country, all else equal, will likely have higher pollution levels. However, a more populated country may not have higher pollution per capita. If population grows faster than pollution levels pollution per capita may actually decrease. Consider, for example, two equally polluted rivers with one in the US and the other in China. The river in China will appear less polluted if the pollution indicator is expressed in per capita terms simply because of China's large population.

This paper controls for pollution in two different ways then compares results. In the first model the pollution indicator is expressed in per capita terms; which is typical in EKC studies. In the second model BOD, measured in kilograms per day, is first regressed on population in a two step estimation. The residual from this first step, representing the BOD pollution not due to population, is used in the second step as the dependent variable. AIC indicates that the second model is preferred to the first model suggesting future empirical EKC studies may benefit by considering the alternative approach to control for population across countries.

References

Alan Heston, Robert Summers and Bettina Aten, Penn World Table Version 6.3, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, August 2009.

Andreoni, J., & A. Levinson. (2001). The simple analytics of the environmental Kuznets curve. Journal of Public Economics, 80(2), 269–286.

Ang, J. B. (2007). CO2 emissions, energy consumption, and output in France. Energy Policy, 35, 4772-4778.

Antle, J.M. & Heidebrink, G. (1995). Environment and development: theory and international Evidence. Economic Development and Cultural Change, 43(3), 603–25.

Antweiler, W., B. Copeland and S. Taylor. (2001). Is Free Trade Good for the Environment. American Economic Review, 91(4), 877-908.

Arrow, K.J., B. Polin, R. Costanza, P. Dasgupta, , C. Folke, C.S. Holling, B.O. Jansson, S. Levin, K.G. Maler, C. Perrings, D. Pimentel. (1995). Economic growth, carrying capacity, and the environment. Science, 268, 520–521.

Auffhammer, M., A. M. Bento, and S. E. Lowe. (2009). Measuring the effects of environmental regulations: The critical importance of a spatially disaggregated analysis. Journal of Environmental Economics and Management, 58, 15–26.

Barua, A and Klaus Hubacek. (2009). An empirical analysis of the environmental Kuznets curve for water pollution in India. International Journal of Global Environmental Issues, 9, 50-68.

Bhattarai, M. and M. Hammig. (2001). Institutions and the environmental Kuznets curve for deforestation: A cross country analysis for Latin America, Africa, and Asia. World Development, 29(6), 995-1010.

Bella, Gianni, C. Massidda, and I. Etzo. (2010): A panel estimation of the relationship between income, electric power consumption and CO_2 emissions. MPRA.

Borghesi, S. (2006). Income inequality and the environmental Kuznets curve, in M. Basili, M. Franzini, and A. Vercelli (eds) Environment, Inequality and Collective Action, Rutledge, London, 33–51.

Brock, W.A.,and M.S. Taylor. (2010). The Green Solow Model. Journal of Economic Growth, 15, 127-153.

Carlsson, F. and Lundstrom, S. (2003). The effects of economic and political freedom on CO2 emissions, Working Papers in Economics 29, Department of Economics, Goteborg University.

Cole, M.A. (2004). Trade, the pollution haven hypothesis and the environmental Kuznets curve: examining the linkages. Ecological Economics, 48, 71–81.

Cole, M.A. and Neumayer, E. (2004). Examining the impact of demographic factors on air pollution, Population and Environment, 26, 5–21.

Cole, M.A. (2000). Air pollution and 'Dirty' Industries: How and Why Does the Comp of Manufacturing Output Change with Economic Development? Environmental and Resource Economics, 17(1), 109-123.

Cole, M., A. Rayner, and J. Bates. (1997). The environmental Kuznets curve: an empirical analysis. Environment and Development Economics, 109, 755–87.

Copeland, B. &Taylor, M. (1994). North-South Trade & the Environment. Quarterly Journal of Economics, 109(3), 755-787.

Cropper, M., and C. Griffiths. (1994). The interaction of population growth and environmental quality. American Economic Review, 84, 250–254.

Dasgupta, S., B. Laplante, H. Wang, and D. Wheeler. (2002). Confronting the environmental Kuznets curve. Journal of Economic Perspectives, 16 (1), 147–68.

de Bruyn, S. (1997). Explaining the environmental Kuznets curve: structural change and international agreements in reducing sulphur emissions. Environment and Development Economics, 2, 485–503.

de Bruyn, S.M. and R.J. Heintz. (1999). The environmental Kuznets curve hypothesis. In Handbook of Environmental and Resource Economics, 656 - 677.

Econstats.com. (3/10/12). http://www.econstats.com/weo/CBOL.htm.

Ekins, P. (1997). The Kuznets curve for the environment and economic growth: Examining the evidence. Environment and Planning, 29, 805-830.

Enders, Walter. (2004). Applied Econometric Time Series, 2nd Edition. John Wiley and Sons. European Commission (2010). http://ec.europa.eu/environment.

Gassebner, Martin , Michael J. Lamlay, and Jan-Egbert Sturmz (2010). Determinants of pollution: what do we really know? Oxford Economic Papers, 1 of 28 doi:10.1093/oep/gpq029

Granda, Catalina, Luis Guillermo Pérez, and Juan Carlos Muñoz. (2008). The Environmental Kuznets Curve for Water Quality: An Analysis of its Appropriateness Using Unit Root and Cointegration Tests. Lect. Econ., 69, 221-244.

Grossman, G. M, and A. B. Krueger. (1991). Environmental impacts of a North American Free Trade Agreement. NBER Working Paper 3914.

Grossmann, G.M., Krueger, A.B. (1995). Economic growth and the environment. Quarterly Journal of Economics, 110 (2), 353–377.

Halkos, George. (2003). Environmental Kuznets Curve for sulfur: evidence using GMM estimation and random coefficient panel data models, Environmental and Development Economics, 8 (4), 581-601.

Helland, E., and A.B. Whitford. (2003). Pollution incidence and political jurisdiction: evidence from the TRI. Journal of Environmental Economics and Management, 46, 403-424.

Hettige, H., R. Lucas, and D. Wheeler. (1992). The toxic intensity of industrial production: Global patterns, trends, and trade policy. American Economic Review, 82, 478–81.

Holtz-Eakin, D., and T. M. Selden. (1995). Stoking the fires? CO2 emissions and economic growth. Journal of Public Economics, 57, 85–101.

Hwang, Hsiang-Chih. (2007). Water Quality and the End of Communism: Does a Regime Change lead to a Cleaner Environment. papers.ssrn.com

Im, K., M. Pesaran, and Y. Shin. (2003). Testing for unit roots in heterogenous panels. Journal of Econometrics, 115, 53-74.

Iwata, H., Okada, K. and Samreth, S. (2010) Empirical study on environmental Kuznets curve for CO2 in France: the role of nuclear energy, Energy Policy.

Jalil, A., Mahmud, S. F. (2009). Environment Kuznets curve for CO2 emissions: a cointegration analysis. Energy Policy 37, 5167-5172.

John, A., and R. Pecchenino. (1994). An overlapping generation model of growth and the environment. *Economic Journal*, 104, 1393–410.

Klick, J. (2002). Autocrats and the environment or it's easy being green, Law & Economics Research Paper 02-16, George Mason University, Washington, DC.

Kremers, J.J.M., Ericson, N.R., Dolado, J.J., (1992). The power of cointegration test. Oxford Bulletin of Economics and Statistics, 54, 325-348.

Lee, C. and Chui, Y. and Sun, C. (2010). The environmental Kuznet's curve hypothesis for water pollution: Do Regions Matter? Energy Policy 38(1), 12-23.

Li, Wang. (2010). A nonparametric analysis on the environmental Kuznet's curve. Environmetrics, 22(3), 420-430.

List, J.A. and C.A. Gallet. (1999). The Environmental Kuznets Curve: Does One Size Fit All? Ecological Economics (31), 409-423.

Lin, Cynthia C. Y. and Zachary Liscow. (2009). On the Political Mechanisms of the Environmental Kuznets Curve for Global Water Quality. Working Paper.

Lopez, R. (1994). The environment as a factor of production: The effects of economic growth and trade liberalization. Journal of Environmental Economics and Management, 27, 163–84.

Maddison, David. (2006). Environmental Kuznets curves: A spatial econometric approach. Journal of Environment and Economics Resources, 51, 218-230.

Managi, Shunsuke, Akira Hibiki, and Tetsuya Tsurumi. (2009). Does trade openness improve environmental quality? Journal of Environmental Economics and Management, 58, 346-363.

Martínez-Zarzosa, I. and Bengochea-Morancho. (2004). Pooled mean group estimation of an environmental kuznets curve for CO_2. Economic Letters, 82, 121-126.

McConnell, K. E. (1997). Income and the demand for environmental quality. Environment and Development Economics, 2, 383–399.

Mythili, G. and Mukherjee, S. (2011). Examining Environmental Kuznets Curve for River Effluents in India. Environment, Development and Sustainability, forthcoming.

Neumayer, E. (2003) Are left-wing party strength and corporatism good for the environment? Evidence from panel analysis of air pollution in OECD countries, Ecological Economics, 45, 203–20.

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

Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. Working Paper WP238, Technology and Employment Programme, International Labour Office, Geneva.

Panayotou, T. (1995)Environmental degradation at different stages of economic Development, in I. Ahmed and J.A. Doeleman, eds., Beyond Rio: The Environmental Crisis and Sustainable Livelihoods in the Third World, ILO Studies Series, New York, (1995): St. Martin’s Press.

Paudel, K. P., H. Zapata, and D. Susanto. (2005). An empirical test of environmental Kuznets curve for water pollution. Environmental and Resource Economics, 31, 325–348.

Pedroni, PL. (2004). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the Purchasing Power Parity Hypothesis, Econometric Theory, 20 (3), 597-625.

Perman, R. and D.I. Stern. (2003). Evidence from panel unit root and cointegration tests that the environmental Kuznets curve does not exist. Australian J. Agr. Resource Econ, 47325–347.

Pesaran, M.H., Shin, Y. (1999). An autoregressive distributed lag modeling approach to cointegration analysis. Chapter 11 in Econometrics and Economic Theory in the 20th century: The Ragnar Frisch Centennial Symposium, StromS (ed.) Cambridge University Press: Cambridge.

Pesaran, M.H., Shin, Y., Smith R. (1999). Pooled mean group estimation of dynamic heterogeneous panels. Journal of the American Statistical Association, 94, 621-634.

Pesaran, M.H., Smith R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics 68, (1), 621-634.

Rupasingha,A., S.J. Goetz, D.L. Debertin and A. Pagoulatos. (2004). The environmental Kuznets curve for US counties: a spatial econometric analysis with extensions. Pap. Reg. Sci., 83, 407–424.

Schmalensee, R., T. M. Stoker, and R. A. Judson. (1998). World carbon dioxide emissions: 1950–2050. Review of Economics and Statistics, 80, 15–27.

Selden, T. M., and D. Song. (1994). Environmental quality and development: Is there an environmental Kuznet's curve for air pollution? Journal of Environmental Economics and Management, 27, 147–62.

Shahbaz, M., Jalil, A & Dube, S. (2010). Environmental Kuznets Curve (EKC): Time series evidence from Portugal. Retrieved from: http://mpra,ub.uni-muenchen.de/ 27443.

Shafik, N., and S. Bandyopadhyay. (1992). Economic growth and environmental quality: Time series and cross country evidence. World Development Working Paper WPS 904., Washington, DC: World Bank.

Sigman, H. (2002). International spillovers and water quality in rivers: Do countries free ride? American Economic Review, 92, 1152–1159.

Stern, D.I., M.S. Common, and E.B. Barbier. (1996). Economic growth and environmental degradation: The environmental Kuznets curve and sustainable development. World Development 24, 1151–1160.

Stern, D. I. and M. S. Common. (2001). Is there an environmental Kuznets curve for sulfur? Journal of Environmental Economics and Environmental Management, 41 (2), 162-178.

Stern, D. (2004). The rise and fall of the environmental Kuznets curve. World Devel. 32, 1419 1439.

Torras, M., and J. K. Boyce. (1998). Income inequality and pollution: A reassessment of the environmental Kuznets curve. Ecological Economics, 25, 147–60.

Trabelesi, Imen. (2012). Is there an EKC relevant to the Industrial Emission of Water Pollution for SEML and EU countries? Environmental Management and Sustainable Development, 1, (1), 2012.

USEPA. United States Environmental Protection Agency. (2/10/12). http://www.usepa.gov.

United Nations Environment Programme Global Environment Monitoring System (GEMS) Water Programme. (3/5/12). http://www.gemstat.org/.

Viguier, L. (1999). Emissions of SO2, NOx, and CO2 in transition economies: Emission inventories and Divisia index analysis. Energy Journal, 20(2), 59–87.

Vincent, R. J., Rozali, B. M. A. and Associates. (1997). Environment and development in a resource rich economy: Malaysia under the new economic policy, Harvard University Press, Cambridge, MA.

Wagner, Martin. (2008). The carbon Kuznets curve: A cloudy picture emitted by bad econometrics? Resource and Energy Economics, 30, 388-408.

Westerlund, J. (2007). Testing for Error Correction in Panel Data. Oxford Bulletin on Economics and Statistics, 69, 709-748.

World Resources Institute. 2007. EarthTrends: Environmental Information. Available at http://earthtrends.wri.org. Washington D.C.: World Resources Institute

Zapata, Hector, and Paudel, Krishna. (2009). Functional Form of the environmental Kuznets curve, in Qi Li, Jeffrey S. Racine (ed.) Nonparametric Econometric Methods (Advances in Econometrics, Volume 25), Emerald Group Publishing Limited, pp. 471-493.