A THEORETICAL AND EMPIRICAL ANALYSIS OF ECONOMIC GROWTH AND ENVIRONMENTAL DEGRADATION

by

JAMES WESLEY BURNETT

(Under the Direction of John C. Bergstrom)

ABSTRACT

In the following dissertation we offer a theoretical and empirical analysis of the relationship between economic growth and environmental degradation. Specifically, we seek to test the Environmental Kuznets Curve (EKC) hypothesis. This hypothesis postulates that pollution emissions follow an inverted-U shaped relationship with per-capita income as a country's economy expands over time.

The goal of this study is to further examine and develop the EKC literature. We begin our analysis by offering a critical review of the literature. Based upon our review we see two main deficiencies within the literature: 1) there is lack of spatial considerations in the empirical literature; and 2) the empirical literature contains empirical irregularities because there is no generally accepted structural (or theoretical) explanation for the economic growth-pollution relationship. In other words, empirical EKC studies consist solely of reduced-form analyses between emissions and income.

To overcome these gaps within the literature we develop two interrelated essays. In the first essay we introduce a spatial-temporal estimation procedure for per-capita CO_2 emissions and per-capita income in the 48 contiguous states within the United States. This procedure consists of a spatial-temporal panel data estimation scheme that controls for spatial and temporal dependence within the data. We find significant evidence that implies per-capita CO_2 emissions follows the inverted-U shaped relationship with per-capita income.

In the second essay we offer a theoretical model that explains how technological diffusion is driving down pollution emissions over a country's economic development cycle. This relatively simple theoretical model seeks to determine which assumptions are necessary to test the hypothesized inverted-U shape of pollution emissions over time.

INDEX WORDS: Environmental Economics, Environmental Kuznets Curve, Pollution Economics, Economic Growth, Greenhouse Gas Emissions, Spatial Econometrics, Endogenous Growth Theory

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JAMES WESLEY BURNETT

BA, College of Charleston, 1999

MA, University of Georgia, 2007

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2011

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JAMES WESLEY BURNETT

Major Professor:	John C. Bergstrom
Committee:	Michael E. Wetzstein Christopher M. Cornwell William D. Lastrapes

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
May 2011

Dedication

I dedicate this work to Amanda, Lucie, and Lily.

Acknowledgements

I would like to thank my dissertation committee for their advice and insightfulness.

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CHAPTER 1. INTRODUCTION

1.1 Problem Statement and Motivation for Research

From an ecological or environmental perspective, the assumption is often made that economic growth is bad for the environment. But, what story does the theory and empirical data tell us? One's intuition may lead to the belief that pollution will continue unabated as a country's economy grows through time. An examination of the empirical relationship between economic growth and pollution, however, often reveals different results as evidenced by the environmental Kuznets curve (EKC) hypothesis. The EKC hypothesis describes the time path that pollution follows through a country's economic development. This hypothesis claims that environmental degradation follows an inverted U-shaped relationship as a country's economy develops over time.

One explanation for the EKC hypothesis is that pollution emissions increase as a country transitions from a largely agricultural economy to an industrial economy. In the early stages of economic development people are too poor to pay for abatement and disregard the environmental consequences of economic growth. As the country's industrial base expands the pollution emissions continue to increase and start to put pressure on the environment. However, as the country's economy continues to expand, its people eventually become wealthier (GDP per capita grows) and they begin to place value on environmental quality (or disutility from pollution).[1] When the marginal disutility from pollution outweighs the marginal utility of income, then the populous begins to demand pollution abatement. Pollution emissions reach a peak when a country's per capita income reaches a certain threshold—i.e., when the emissions have reached a level no longer considered tolerable by its people. The people then begin to form environmental regulations often through a collective decision-making process. Thus, the EKC hypothesis implies that economic growth could actually be compatible with environmental improvement if appropriate policies are adopted.

The story seems plausible enough on the surface, but testing this hypothesis becomes increasingly more complicated when one considers the empirical or theoretical issues driving the relationship between economic growth and the environment. Since the conception of the hypothesis, researchers have examined a wide variety of pollutants seeking evidence of the EKC. Separate studies have experimented with different econometric approaches, including: different orders of polynomials, fixed and random effects, semi-parametric and non- parametric techniques, splines, and different covariates specifications. Past studies have also examined different jurisdictions and time periods.

In all there has been over 100 peer-reviewed journal articles published in the past two decades related to the EKC hypothesis (Yandle, Madhusudan, & Vijayaraghavan, 2004). Certain generalizations seem to emerge across these different approaches—i.e., it seems that pollution levels at least approximately improve for

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[1] This theoretical explanation implies two income effects: one, an increase in income changes preferences so as to increase demand for pollution abatement; or two, an increase in income relaxes the budget constraint so that the households can afford abatement.

some pollutants as income per capita grows. The lasting contribution is that EKC literature has shifted the conventional wisdom of many economists and policymakers towards a belief that economic growth can actually be good for the environment (Carson, 2010).

Despite the relatively robust body of EKC literature one particular problem still remains—the examined empirical models are composed of a reduced-form equation. In other words, there is no general consensus on a structural equation or theory that explains the relationship between economic growth and environmental quality. To make up for the gap in theory several structural (or theoretical) models have been formulated in conjunction with the empirical approaches to find evidence of the inverse-U shaped relationship. These theoretical models range from simple static models to relatively complex economic growth models. What is missing in the theoretical EKC literature is an explanation for the source of change in economic growth and how the source is related to pollution emissions. We posit that the diffusion of technology and environmental policy can be compatible with economic growth and that both have direct effects on pollution levels.

Our goal is to further the economic growth-pollution relationship analysis by positing that income alone is not sufficient to explain the difference in the reduction of pollution levels across countries—in this manner we seek to move beyond the traditional EKC explanation for the relationship between economic growth and pollution. We contend that international exchange has opened channels of communication that facilitate the transmission of policy and technical information. Environmental policy constitutes a large part of these open communications between industrialized and developing countries. It is possible then that the communication about environmental policy and the transmission of certain technical information (namely less pollution-intensive forms of production) has led to reductions in pollution in developing countries. In this sense technological diffusion coupled with environmental policy is largely responsible for the reduction in pollution levels. Intuitively, one can think of this as a dual effect within a closed economy. On one hand the growing awareness of environmental issues (such as global warming) prompts the private sector to invest resources towards research and development (R&D) to invent technologies that are more environmental efficient or less pollution intensive.[2] On the other hand concerns over environmental problems prompts the populous to engage in some sort of collective decision-making process in which environmental policies are formulated.

One of the results of the collective decision-making process, prompted by the increased public concern for environmental quality and demand for pollution abatement, is the creation of third-party regulators of pollution such as the Environmental Protection Agency in the United States. Environmental quality is considered a public good so the third-party regulator's role is to allocate the efficient amount of environmental quality to society. Analogously, pollution is a public bad and the third-party regulator's role is to allow the efficient amount of pollution to remain in the environment. Looked at either way, the regulator regulates the output of pollution from production within the private sector (pollution abatement policies)

[2] These new technologies often have the dual effect in which they are more production efficient as well. These new technologies can either be thought of as new patented inputs in the production process or the advent of new production processes. We will discuss this in further detail in Chapter 4.

and may also offer subsidies to R&D investment for the innovation of more environmental efficient products or production processes.

This argument is consistent with the traditional EKC hypothesis in the sense that per-capita income must reach a minimum threshold before a reduction in pollution can occur.[3] However, income alone is not sufficient—instead we mean to show that environmental policy coupled with the diffusion of technology drives the economic growth-pollution relationship.[4] In other words, we seek to explain the source that drives down pollution levels as an economy expands over time. In this sense we are moving beyond the traditional EKC explanation of how economic growth is related to pollution.

It should be noted that we are not discounting the traditional EKC explanation completely. We believe that there are still valuable insights to be gained from this explanation. For example, are local pollution emissions affected by neighboring spatial spillovers or transboundary pollution problems? If so, what are the policy implications for transboundary pollution?

1.2 Objectives

The overall purpose of this dissertation is to theoretically and empirically address the question: What is the relationship between economic growth and environmental degradation (pollution) over time? The specific objectives for addressing this overall research question are: (1) empirically test the traditional environmental Kuznets curve

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[3] If the majority of a country's populous is in extreme poverty, then the adoption of pollution regulations is too costly to justify

[4] This argument also is consistent with the EKC explanation that international trade could alter the ―composition" of economic activity and change the ―techniques" of production for a developing country (Grossman & Krueger, Environmental Impacts of North American Free Trade Agreement, 1991).

(EKC) hypothesis accounting for spatial and temporal effects; and (2) to develop an alternative theoretical model explaining decreasing environmental pollution with increasing economic growth incorporating the role of technological change within a closed economy.

1.3 Structure of the Study

The rest of this dissertation is organized as follows. Chapter 2 will: (a) offer a brief critical review of the literature; (b) offer a general theoretical framework for modeling the EKC hypothesis; and (c) introduce new theoretical and econometric approaches to modeling the EKC relationship.

Chapters 3-4 will develop two interrelated essays related to the decreasing environmental pollution with increasing economic growth debate. Chapter 3 will add to the literature by offering a newly developed spatial-temporal estimation scheme for the economic growth-pollution relationship. Chapter 4 will provide a theoretical model of the role of technology in a closed economy and the relationships between economic growth and pollution as a public bad (or environmental quality as a public good).

Chapter 5 will: (a) summarize and conclude the main findings of this dissertation; (b) compare the findings to previous studies; (c) discuss contributions of this research to the literature and policy implications; and (d) offer suggestions for future research.

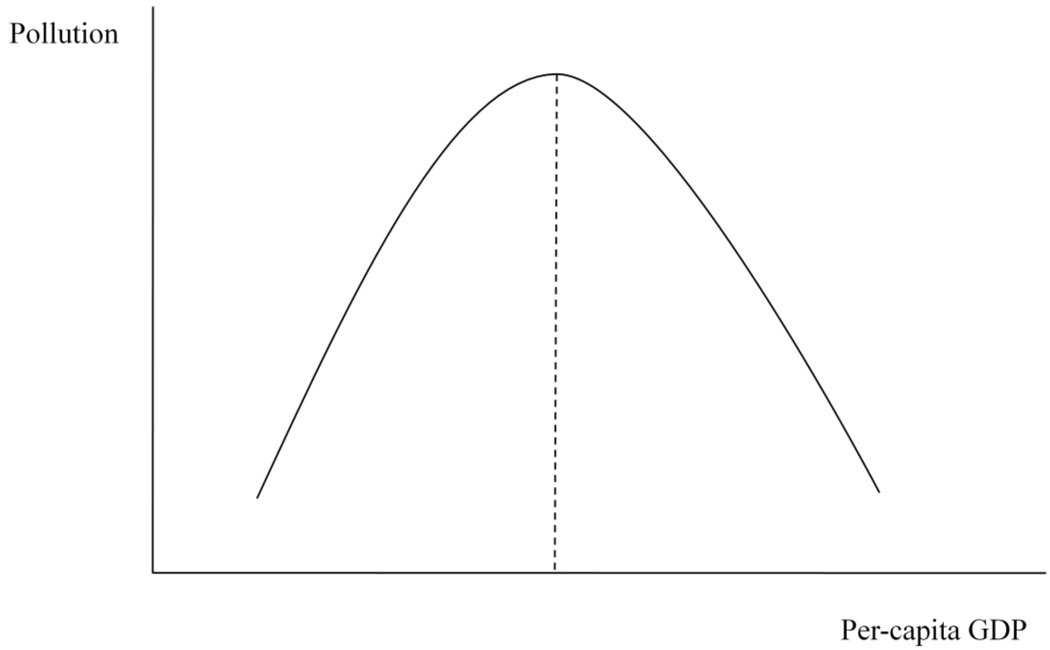
CHAPTER 2. WHAT DO WE REALLY KNOW ABOUT THE ENVIRONMENTAL KUZNETS CURVE? A CRITICAL REVIEW OF THE LITERATURE

2.1 Introduction

Economists, ecologists, private industries and government decision-makers have long been interested in the relationship between economic growth and environmental quality. This relationship is often the subject of intense public policy debates such as the Copenhagen Treaty signed by the current U.S. Presidential Administration at the 2009 U.N. Climate Change Conference. Under this treaty the Administration has proposed to cut greenhouse gas (GHG) emissions in the U. S. by 17% by 2020 and 42% by 2030. In the U.S. many opponents to this legislation claim it will further slow the recessionary economy experienced in the country over the past two years. Supporters, on the other hand, claim the legislation is absolutely necessary to prevent irreversible global warming caused by anthropogenic emissions of greenhouse gases. We pose the question: is it possible for an economy to continue to grow and experience a reduction in GHG emissions with the enforcement of such policies?

According to the environmental Kuznets curve (EKC) hypothesis, economic growth itself may be a vehicle that reduces pollution emissions. The EKC hypothesis describes the time path that pollution follows through a country's economic growth. This hypothesis claims that environmental degradation follows an inverted U-shaped relationship as a country's economy grows over time as displayed in Figure 2.1 below.

Figure 2.1. Environmental Kuznets Curve



The purpose of this chapter is to provide a brief critical review of the existing the EKC literature. We will expound upon the theoretical work by dissecting the environment into its separate components in an attempt to better understand the relationship between pollution emissions and economic growth. This chapter is not intended to be a complete survey of the EKC literature but rather a brief review with special attention paid to key aspects within the literature. Based on our review we will offer suggestions for future EKC research.

The rest of this chapter is organized as follows. In Section 2.2 we will explore a general theoretical framework of the EKC hypothesis. Section 2.3 will discuss the origin of the pollution vs. economic growth debate and the conception of the EKC hypothesis. Section 2.4 will look at the basic methodological approaches adopted in the EKC literature and briefly review past findings. In Section 2.5 we offer a brief critical review of the existing literature which we motivate through the use of flow charts. Based upon our criticism, we will suggest a new theoretical approach to model the economic growth-pollution relationship.

2.2 General Framework

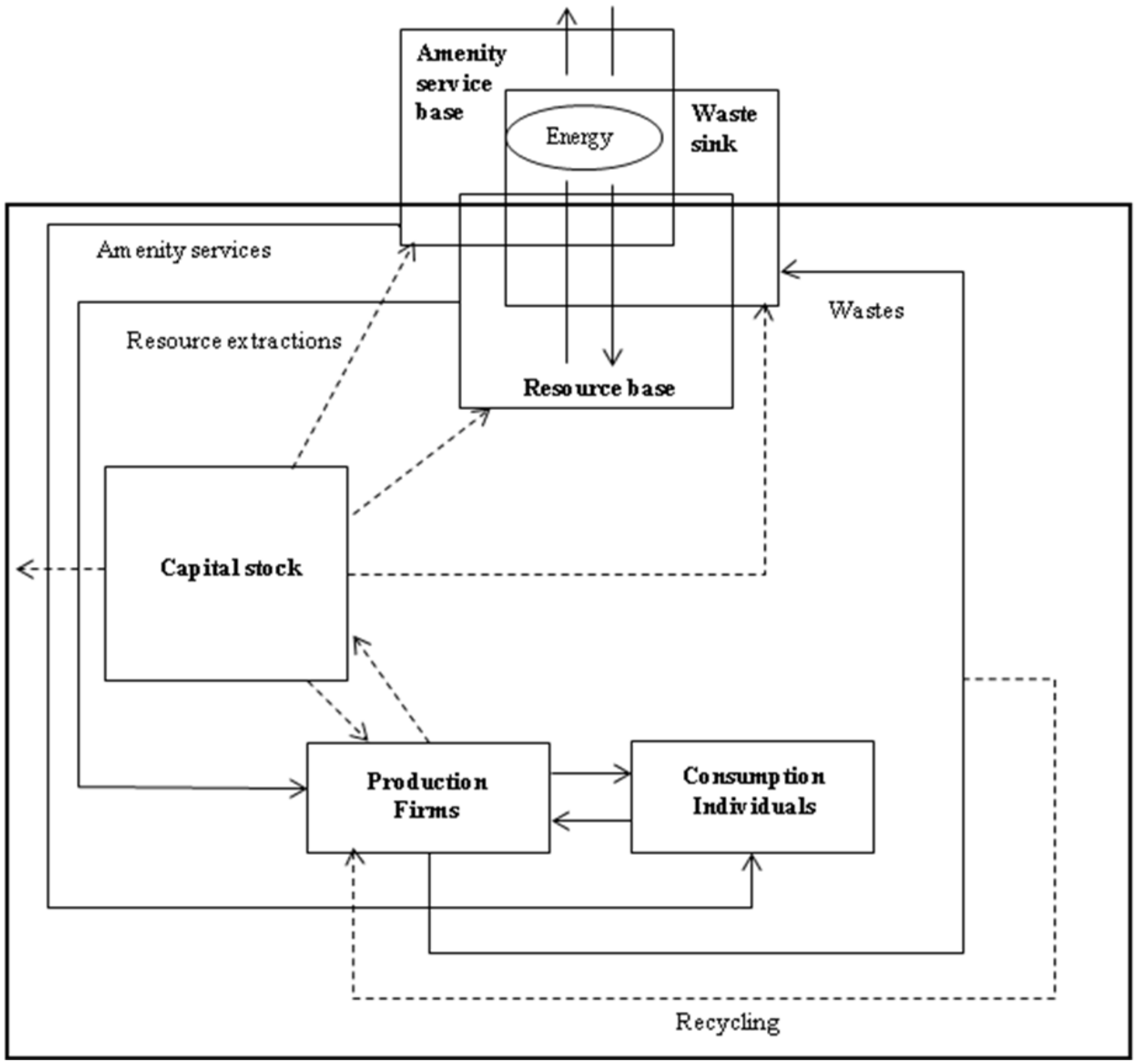
In order to better understand the EKC hypothesis it would be a useful exercise to examine how the various parts of the economy and the environment interact; i.e., decompose the environment into its various parts. The decomposition of the relationship can better be understood by examining an environmental circular flow diagram including pollution (waste) and the economy. Figure 2.2 offers a diagram representing the two-way relationship between the economy and the environment.[5]

The circular flow diagram in Figure 2.2 may look daunting at first glance, but it somewhat accurately reflects the relationship between the economy and the environment. This diagram shows the linkages among the capital stock, production, and consumption. The outer heavy black box represents the environment. The environment receives solar radiation and reflects some of it back into space—this relationship is captured by the two arrows at the top of the diagram. This radiation ultimately drives environmental processes. The arrows pass through three boxes which represent three major functions of the environment (Perman et al., 2003). The heavy line outer box, the fourth function, represents the provision of life-support services within the environment. The economy operates within the environment through consumption and production by drawing upon environmental services—this

[5] This diagram is taken from Perman et al. (2003).

is represented by the solid lines. Production also functions by drawing upon resources which are extracted from the environment. Production and consumption give rise to waste (some of which is recycled) which is returned to the environment. Consumption also directly draws upon amenity services offered by the environment.

Figure 2.2. Economic Activity in the Natural Environment



The environment (the heavy line box outlining the diagram) operates as a resource base, amenity base, and waste sink (represented by the three boxes at the top). These functions offer the basic life-support function for humans. As a waste sink, the environment (or ecosystem) has a natural ability to dissipate some harmful air, water, and solid pollutants; however, when the environment's ability to dissipate or absorb pollution (the carrying capacity) is exceeded, then environmental quality will fall and policy responses made by the government may in turn slow economic growth in the long run (Brock & Taylor, 2004).

Upon looking at the complex circular flow diagram in Figure 2.2, it seems that nothing valuable could potentially be gained by simply regressing the flow of wastes (or pollution) on total economic activity because there are so many other intervening factors in the economy (and/or the environment) that may affect the relationship between economic growth and pollution. In other words, an empirical approach may not entirely inform us of the true relationship between pollution and economic growth because it is simply a reduced-form regression. The development of a structural model including the economic agents, markets, and pollution could potentially offer a far better explanation of the relationship between economic growth and pollution.

2.3 Origin of the Debate

The origin of the debate between economic growth and environmental degradation dates back as far as the 18th century but it reemerged in the early to mid 20th century. With the growing environmentalist movement in the U.S. and across the world, economists were becoming more aware of how economic growth may affect the environment or natural resources (the natural world). The negative effects of economic growth on the environment were enumerated in the works of several authors including Mishan (1967), Schumacher (1973), and Hirsch (1977). Moreover, the oil crisis of 1973 made people acutely aware of how natural resources are a determining factor in economic growth. As a consequence of this growing awareness, two debates began to emerge concerning the relationship between economic growth and the natural world.

The first debate, outlined in the classic monograph *The Limits to Growth*, concerned the planet Earth's limited natural resource base. In this work the authors posited that the planet's limited resources could no longer support unfettered economic growth (Meadows et al, 1972). In other words, the authors argued that there were biophysical limits to growth. The limits-to-growth argument was highly controversial but it captured the attention of the popular imagination in the 1970s. This argument would later be refuted by several economists including Nordhaus et al, (1992).

The other debate which received less attention concerned nature's role as a sink to capture pollution and waste caused as a by-product of economic activity (Brock & Taylor, 2004). This argument asserts that if the environment is no longer able to dissipate or absorb wastes (including pollutants) then environmental quality will fall, and policies will have to be put in place to deal with the environmental damages. Such policies will in turn affect economic growth.

By the 1980s, economists became more optimistic about technological advancement as a solution to conflicts between economic growth and the natural world. Technology then began to dominate the macroeconomic models of this relationship. For example, Baumol and Blackman (2002) argued that technological change leads to rising productivity which could reduce the drawdown of the stock of natural resources. Aghion and Howitt (1998) later implied that “intellectual capital” could potentially counterbalance the biophysical constraints on economic activity.

2.3.1 Conception of the EKC Hypothesis

Starting in the 1990s, attention shifted from the limits-to-growth debate towards growing optimism in globalization as a means for a developing country to “grow out” of its environmental problems. Grossman and Krueger (1991) examined the environmental impacts of the North American Free Trade Agreement (NAFTA). The authors argued that NAFTA could affect pollution emissions through scale, composition, or technique effects. The scale effect captures how trade liberalization could stimulate economic expansion, and if the structure of economic activity does not change then the scale of pollution would be expected to increase. The composition effect explains how pollution emissions may change when trade liberalization changes the structure of economic activity within a country. For example, international trade has led to a change in the structure of the U.S. economy from a manufacturing base to largely a service base. The technique effect refers to a change in production technologies caused by trade liberalization (and foreign direct investment). For example, foreign direct investment my lead to cleaner production technologies in developing countries.

Putting the above effects together, the authors asserted that trade liberalization could expand the Mexican economy (scale effect) which may lead to structural changes in production (compositional and technique effects) which in turn may improve environmental quality within Mexico, a developing country. To test if trade liberalization leads to environmental improvement the authors examined the relationship between pollution emissions and per capita GDP in 42 separate countries (Grossman & Krueger, 1991). The authors discovered a systematic relationship between pollution emissions and national income which showed that some environmental air quality indicators actually improved as national income and consumption levels increased.

Grossman & Krueger's (1991) hypothetical relationship would later be named the environmental Kuznets hypothesis after the work of Simon Kuznets (1955) who discovered an inverse-U shaped relationship between income inequality and per capita income. In contrast to the limits-to-growth argument, the results of Grossman and Krueger (1991; 1995) seemed to imply that higher levels of national income could actually lead to a reduction in environmental degradation. Their findings raised the intriguing and at least to some counter-intuitive policy implication that economic stimulus measures could be more effective than slow-growth or no-growth sustainability measures in curbing pollution emissions in developing countries. Shafik and Bandyopadhyay (1992) conducted a similar cross-country analysis by examining patterns of environmental quality for countries at different income levels. The authors found that income (national GDP) was the most significant indicator of environmental quality; however, the authors claimed that the relationship between environmental quality and economic growth is far from simple. The authors argued that some countries were able to ―grow out of" environmental pollution problems with economic growth. However, they posited that the process is not necessarily automatic and intentional policies and investments are necessary to ensure reduced environmental degradation (Shafik & Bandyopadhyay, 1992).

2.4 Specific Methodological Approaches

Since the conception of the EKC hypothesis, there have been two primary methodological approaches to studying the hypothesized relationship. The first approach is to develop an empirical model based on a reduced-form relationship between pollution and economic growth. The goal of the first approach is to *induce* a relationship between pollution and economic growth based upon the empirical data. The second approach is to develop a theoretical or structural model based on a rigorous set of assumptions. The goal of the second approach is to *deduce* a relationship between economic growth and pollution.

Grossman & Krueger (1995) point out that the first approach is advantageous because: (a) it yields the net effect of a nation's income on pollution; and (b) it is not necessary to gather hard data on pollution regulations, state of technology, etc. They argue that the limitation of the reduced-form approach is that it is unclear why the estimated relationship exists.

2.4.1 Empirical Approach

Starting with Grossman and Krueger (1991, 1995), one of the most common empirical methodological approaches to testing the environmental Kuznets curve hypothesis has been to specify a panel data regression model to induce a relationship from the empirical data. This specification is generally expressed as

$$y_{it} = X_{it}\beta + \mu_i + \eta_t + \varepsilon_{it,} \qquad (2.1)$$

where y_{it} denotes the environmental indicator (such as a particular water or air pollutant), X_{it} denotes an (N x K) matrix of explanatory variables, β is a (K x 1) vector of coefficients on the explanatory variables, μ_i denotes cross-sectional dummies that capture unexplained heterogeneity between jurisdictions, η_t denotes time dummies to control for time trends, and ε_{it} denotes the idiosyncratic error term. The subscript i represents a particular jurisdiction (such as a country) and t is time. The explanatory variables usually contain a quadratic specification of national income (generally measured as GDP, per-capita GDP, or the natural log of GDP) and other control variables such as population density, trade indicators and political freedom (Carson, 2010). The unexplained heterogeneity term captures systematic or structural differences across jurisdictions; these differences are generally assumed to be relatively fixed.[6] The ultimate goal of course is to find out which part of the variation in the dependent variable y_{it} (environmental indicator) can be attributed to changes in national income.

One of the subtle problems with the specification in (2.1) is that it imposes homogeneity over the independent variables across the different cross-section (i.e., there are no subscripts on the coefficients of the explanatory variables—the coefficients are assumed to be fixed).[7] This homogeneity amounts to assuming that each jurisdiction's economic growth-pollution relationship is identical. This assumption is not so problematic when jurisdictions are fairly similar such as examining individual states within the U.S.; but the assumption becomes more questionable when measuring across countries with vastly different characteristics. In the past it was difficult to gather a large data set of pollution emissions (along the time dimension) within individual jurisdictions, so panels were used to expand the available data. Today, however, pollution data is much more readily available and in

[6] An alternative estimation scheme is the random effects model which assumes that μ_i is random (not fixed) and therefore should be estimated. Random effects model are relatively rare in the EKC literature.

[7] This specification does allow for some heterogeneity if there is a country-specific intercept.

increasing larger time dimensions within each jurisdiction. Thus, if the homogeneity assumption is overly restrictive then perhaps (assuming the time dimension is large enough) the economic growth-pollution relationship should be estimated individually within jurisdictions and then compared across.

The typical parametric approach to identify equation (2.1) may be formulated as

$$y_{it} = \beta_o + GDP_{it}\beta_1 + GDP_{it}^2\beta_2 + Z\gamma + \mu_i + \eta_t + \varepsilon_{it,} \qquad (2.2)$$

where Z is a matrix of control variables which contains a vector γ of coefficients. To test the robustness of the specification in (2.2) some researchers add a third cubed term of GDP (i.e., GDP_{it}^3) to determine if emissions may improve initially but then worsen over time. The cubic specification of income is sometimes found to be significant but Carson (2010) argues that this is probably the case because there is flattening of the right side of the tail between the economic growth-pollution relationship. Due to this flattening the cubic specification sometimes offers a better approximation than the quadratic, but this does not mean that the cubic specification is the true relationship.

Model (2.2) can be estimated using any standard panel data technique such as fixed effects (the *within* estimator), first-differencing models, random effects, or least squares dummy variable estimation.[8] Moreover, the model allows for testing several forms of the economic growth-pollution relationship (controlling for the other explanatory variables):

[8] The least square dummy variable method can suffer from issues of multicolinearity if both i and t are large.

(i) $\beta_1 = \beta_2 = \beta_3 = 0$ Indicates no relationship between economic growth and pollution.

(ii) $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$ Indicates a monotonically increasing relationship between economic growth and pollution.

(iii) $\beta_1 < 0$ and $\beta_2 = \beta_3 = 0$ Indicates a monotonically decreasing relationship between economic growth and pollution.

(iv) $\beta_1 > 0, \beta_2 < 0,$ and $\beta_3 = 0$ Indicates an inverted-U shaped relationship; i.e., the EKC.

(v) $\beta_1 < 0, \beta_2 > 0,$ and $\beta_3 = 0$ Indicates a U-shaped relationship.

(vi) $\beta_1 > 0, \beta_2 < 0,$ and $\beta_3 > 0$ Indicates a cubic polynomial or N-shaped relationship.

(vii) $\beta_1 < 0, \beta_2 > 0,$ and $\beta_3 < 0$ Indicates the opposite of the N shaped relationship.

Thus, the EKC is only one of the possible outcomes of the model. The turning point for environmental degradation from the EKC hypothesis is obtained in (iv) as:

$$x^* = -\frac{\beta_1}{2\beta_2}. \tag{2.3}$$

Since Grossman & Krueger's (1991) seminal work, researchers have examined a wide variety of pollutants seeking evidence of the EKC. These findings are summarized in Table 2.1 below which was adapted from the work of Lieb (2004). Certain generalizations seem to emerge across these different approaches—i.e., it seems that pollutions levels at least approximately improve for some pollutants as income per capita grows (Levinson, 2008). This generalization can be seen in Table

2.1 as many of the past EKC studies seem to find evidence of the inverted-U shaped relationship between pollution and economic growth. Although as Lieb (2004) points out the validity of this relationship seems to break down when the pollutant is a stock emission such as carbon dioxide. We can see in Table 2.1 that only a few studies find the purported EKC relationship (i.e., the inverted U-shaped relationship) when the pollutant is a stock pollutant.

Table 2.1. Empirical Results for the PIR of Several Pollutants

	Flow pollutants						Stock pollutants	
	SO_2	SPM	NO_x	CO	RP		Waste	CO_2
Grossman and Krueger (1993)	∩	N						
Selden and Song (1994)	∩	∩	∩	is				
Shafik (1994)	∩	∩			N		↗	↗
Grossman (1995)	N	∩	∩	∩				
Grossman and Krueger (1995)	N	∩			∩			
Holtz-Eakin and Selden (1995)								↗
Panayotou (1995)	∩	∩	∩					
Carson et al. (1997)	∩	∩	∩	∩				∩
Cole et al. (1997)	∩	∩	∩	∩	∩		↗	↗
Lim (1997)	∩	∩	∩		∩			↗
Moomaw and Unruh (1997)								N
Panayotou (1997)	N							
Roberts and Grimes (1997, p. 192)								↗
Kaufmann et al. (1998)	N							
Schmalensee et al. (1998)								∩
Scruggs (1998)	∩	∩						
Torras and Boyce (1998)	N	∩			∩			
Wu (1998)		∩						
Agras and Chapman (1999)								∩ / ↗
Barrett and Graddy (2000)	N	∩			∩			
Cavlovic et al.(2000)	∩	∩	∩	∩	∩			↗
Cole (2000, p. 112)	∩		∩					
Dinda et al.(2000)	∩	N						
Hettige et al. (2000)				∩				
List and Gerking (2000)	∩		∩					
Perrings and Ansuategi (2000)	∩							↗
Halkos and Tsionas (2001)								↗
Heil and Selden (2001)								↗
Minliang et al. (2001)							↗	
Roca et al. (2001)	N		is					↗
Stern and Common (2001)	∩ / ↗							↗
Hill and Magnani (2002)	∩		∩					∩ / ↗
Friedl and Gletzner (2003)								N
Millimet et al. (2003)	∩		∩					

Note: SPM – suspended particulate matter; RP – river pollution; ∩ – EKC; ↗ – the pollution-income relationship (PIR) is monotonically rising or the EKC has an out-of-sample turning point; N – the PIR is N-shaped (first rising, then falling, and finally rising again) with both turning points inside the sample range; is – insignificant; ∩ / ↗ — results of two different estimations (environmental Kuznets curve and monotonically rising)

2.4.2 Theoretical Approach

Andreoni and Levison (1998) developed one of the earlier theoretical approaches which stands out for its simplicity and underlying intuition. In this study the authors specify a simple static model based on microeconomic foundations of the economic growth-pollution relationship. Their model was composed of one single agent (representative household) in the economy that gets utility from consumption of a private good, *C*, and disutility from pollution, *P* which is in the nature of a public ―bad" or undepletable negative externality, according to the following assumptions for preferences

$$U = U(C, P). \quad U_c > 0,\ U_p < 0 \tag{2.4}$$

Further, they assume that *U* is quasi-concave in *C* and –*P*. The authors assume that pollution is a by-product of consumption, and the agent has a means of alleviating pollution by extending resources to clean it up; they define the pollution alleviating activities as *E*, for environmental effort. Pollution then is a positive function of consumption and a negative function of environmental effort

$$P = P(C, E). \quad P_c > 0,\ P_E < 0 \tag{2.5}$$

The authors finally assume a resource constraint where *M* is the limited endowment of resources spent on *C* and *E*; therefore, the constraint is $C + E = M$. The authors illustrate a simple example by specifying the functional forms of utility and pollution as follows

$$U = C - zP \tag{2.6}$$

$$P = C - C^{\alpha} E^{\beta} \tag{2.7}$$

where z is a (strictly positive) constant marginal disutility of pollution and $C^{\alpha}E^{\beta}$ is a standard concave production function of abatement. By setting $z = 1$, substituting (2.7) into (2.6) and maximizing the abatement production function subject to the resource constraint, the authors are able to derive the optimal quantity of pollution (Andreoni & Levinson, 1998):

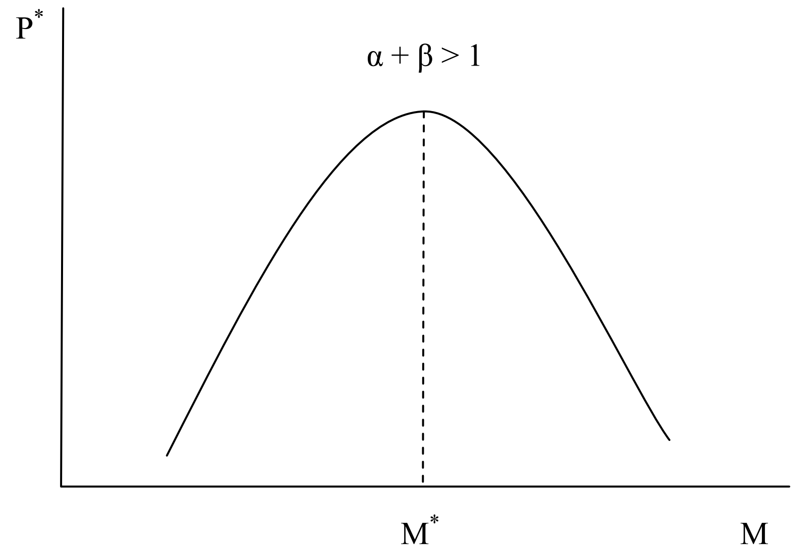
$$P^*(M) = \frac{\alpha}{\alpha+\beta}M - \left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\beta}{\alpha+\beta}\right)^{\beta} M^{\alpha+\beta} \tag{2.8}$$

According to the authors, the derivative of (2.8) is the slope of the environmental Kuznets curve

$$\frac{\partial P^*}{\partial M} = \frac{\alpha}{\alpha+\beta} - (\alpha+\beta)\left(\frac{\alpha}{\alpha+\beta}\right)^{\alpha}\left(\frac{\beta}{\alpha+\beta}\right)^{\beta} M^{\alpha+\beta-1} \tag{2.9}$$

the sign of which depends on the parameters α and β . The authors conclude that if $\alpha + \beta > 1$, then the abatement technology exhibits increasing returns to scale (IRS), and *P*(M)* is concave as in Figure 2.3 below.

Figure 2.3. Environmental Kuznets Curve with IRS Abatement Technology



The graph in Figure 2.3 is what is described as the environmental Kuznets curve. Further, the authors find that the economic growth-pollution relationship (where economic growth is indicated by increasing M) is linear if there are constant returns to scale and U-shaped if there are decreasing returns to scale. The authors cite empirical evidence from coal-fired power plants which suggests that increasing returns to scale may be the norm in that industry.

Other than the work of Andreoni and Levinson (1998), several other theoretical models have been developed including other static models (Stockey, 1998; Lopez, 1994), Solow growth models, endogenous growth models, and overlapping generation models. The latter three models differ from the static ones in that they are dynamic allowing for consumption, production, and pollution to be analyzed intertemporally. The Solow growth models follow the first generation of the neoclassical growth models (Brock & Taylor, 2004). The endogenous growth models and overlapping generation models follow new growth theory in which technology is endogenized; this is opposed the Solow models which assume that technological growth is exogenous. The overlapping generation models are important for considering issues of environmental quality and intergenerational equity (John & Pecchenino, 1994; Jones & Manuelli, 1995). The endogenous growth models largely ignore intergenerational equity in favor of modeling the source of growth in the economy and its effect on the environment (Selden & Song, 1995; Stockey, 1998; Chimeli & Braden, 2005).

To date the practical lessons from these models are still somewhat limited. These models often find the inverted-U shaped relationship and succeed by making several simplifying assumptions (Levinson, 2008). Thus, there is still no general consensus on a structural model that explains the economic growth-pollution relationship. This deficiency within the theory allows for considerable room for improvement in developing an adequate theoretical model to explain the EKC phenomenon.

2.5 Limitations within the Literature

Based upon our review of both the empirical and theoretical EKC literature outlined in the two previous subsections (2.4.1 and 2.4.2) we see two major deficiencies: 1) the lack of spatial-temporal considerations within the empirical literature; and 2) the lack of development of technological growth models in the theoretical literature.

To the authors' knowledge only two past studies within the empirical EKC literature have addressed the first deficiency within the data. Rupasingha et al. (2004) found evidence for the EKC hypothesis for toxic wastes at the US county level. Maddison (2006) found evidence for the EKC with nitrogen and sulphur dioxide. He argued that national per capita emissions of sulphur dioxide and nitrogen oxides are heavily influenced by the per capita emissions of neighboring countries. He even goes further to claim that a lack of spatial considerations may account for parameter instability in some past studies.

The works of Rupasingha et al. (2004) and Maddison (2006) have made great strides in expanding the current empirical EKC literature, but both are basically static in nature.[9] Works such as Perman and Stern (2003) and Egli (2004) have pointed to the importance of temporal considerations within the empirical literature. We conclude therefore that a richer examination of the EKC hypothesis would involve considerations towards the spatial and temporal aspects within the data. Based upon this conclusion we propose a spatial-temporal panel data estimation scheme for the EKC hypothesis. We motivate this estimation scheme by examining state-level CO_2 emissions in the contiguous United States in Chapter 3 of this dissertation.

The second deficiency takes place within the theoretical EKC literature. Past authors have made great strides in expanding the theoretical literature to include macroeconomic new growth theories, yet the literature still lacks a sufficiently complex endogenous growth model which endogenizes technological advancement. Brock and Taylor (2004) offer a ―Green Solow Model” which is interesting but treats technological growth as exogenous. Chimeli and Braden (2005) offer an endogenous growth model in which they model technological innovation (total factor productivity) through the so called ―AK” model. *A* denotes the ―productivity parameter” (or in their model total factor productivity) and *K* denotes capital.[10] The

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[9] Maddison's (2006) work takes two years of data and differences the data to incorporate the spatial considerations. Therefore his study is dynamic, yet it lacks a richer set of dynamics by not considering multiple years.

[10] We will define and further discuss total factor productivity in Chapter 4.

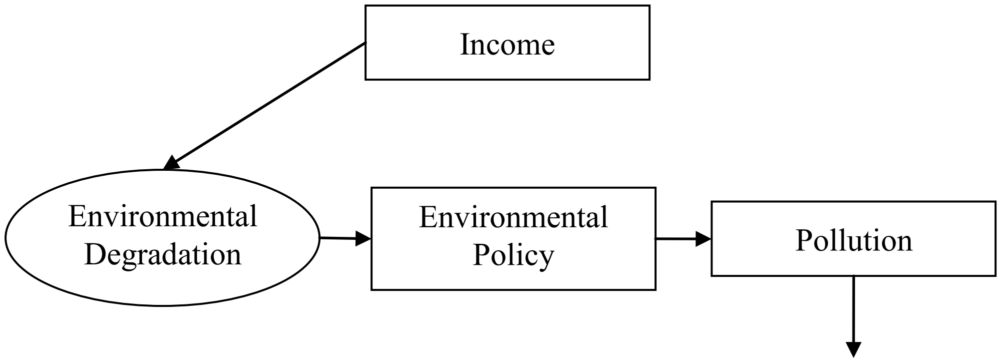
productivity parameter can be interpreted as learning-while-doing in the production process; in other words, a producer becomes more efficient with production over time because she learns while on the job.[11]

While the works of both Brock and Taylor (2004) and Chimeli and Braden (2005) expand the theoretical literature, a richer explanation for the reduction in pollution emissions over time may come from an analysis which directly models technological advancement. We offer such an analysis by modeling technological advancement as an expansion of current technologies in the marketplace. In other words, the market consists of existing dirty technologies which are augmented by newer cleaner technologies. When firms choose these cleaner technologies, then pollution emissions are expected to fall while the economy is continuing to expand over time.

To help motivate the argument for how an expansion in technologies leads to a decrease in pollution we offer the flow diagrams in Figures 2.4 and 2.5 below. The traditional EKC explanation is offered in Figure 2.4, which claims that per-capita income levels drive the reductions in emissions. In other words, as explained in Chapter 1, as a country reaches a certain threshold level of per-capita income, then the marginal disutility from pollution outweighs the marginal utility from income. In this sense the reduction in pollution is largely driven from consumption in the economy. The following diagram (Figure 2.4) helps illustrate this argument.

[11] If knowledge, A, is multiplicative with capital, K, then it is said to be *capital augmenting*. In contrast, A is Hicks-neutral technological progress when the marginal and average products of capital increase in the same proportion.

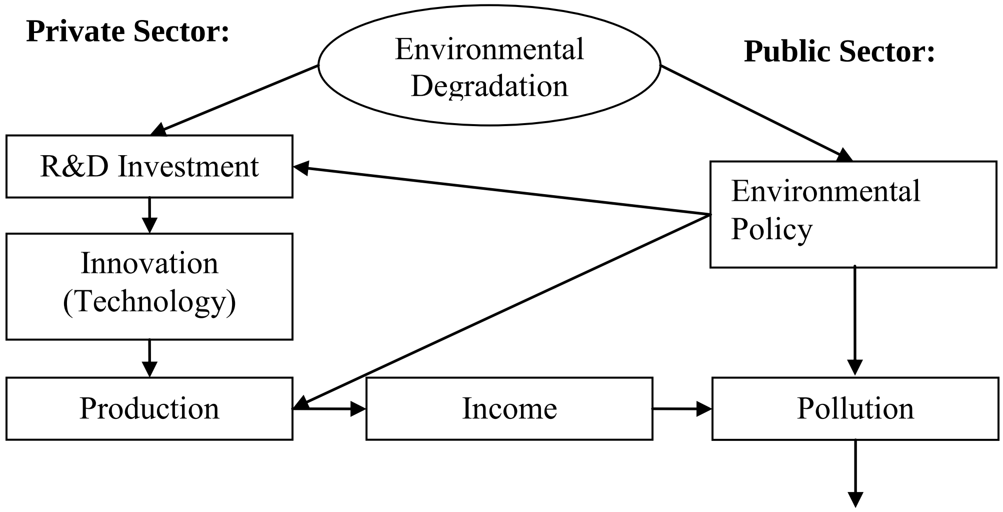
Figure 2.4: Traditional Explanation



As can be gleaned from this flow chart, an increase in income leads the populous to become more aware potential environmental problems because generally as per capital income levels increase, education (including environmental education) increases as well. In addition, increasing per capita income makes environmental quality (which for many people may be in the nature of a ―luxury good") more affordable. This growing awareness, appreciation and affordability of environmental quality often leads to a social decision-making process which culminates into the creation of environmental policies, which in turn reduce pollution levels. This explanation arguably implies that reductions in pollution are a function of income alone. The problem is that several other factors could be driving the process for reductions in pollution (e.g. research and development of pollution-abating technologies) which are not captured in traditional EKC models that are only composed of a reduced form relationship.

The current study seeks to move beyond traditional EKC models by exploring the actual source of the reductions of pollution within the economy. We posit that the economic growth-pollution process and relationship follows something more akin to the flow chart in Figure 2.5 below. Our argument is that awareness of environmental problems such as global climate change has induced countries to engage in R&D investment to develop more environmentally efficient (less pollution intensive) technologies. These new technologies often have the dual effect in which they are more environmentally efficient as well as more productively efficient. Therefore these technologies increase production levels which in turn increase income levels. Moreover, because these technologies are also environmentally efficient, overall pollution levels decrease. Further, we argue that environmental quality is a public good and pollution (a public “bad”) is a by-product of production. This pubic bad (or undepletable negative externality) by-product constitutes a market failure in that producers do not incorporate the full social costs of pollution into their individual cost functions. Therefore, a third-party regulator must allocate the socially efficient amount of pollution in the economy. In its capacity the regulator institutes pollution-abating policies that reduce production levels in the private sector. The same regulator however can offer subsidies to the R&D subsector to develop technologies that more environmentally efficient. The net effects are believed to yield an increase in production and a decrease in pollution.

Figure 2.5: Non-traditional Explanation



Based upon our non-traditional argument we construct an economic growth model in Chapter 4 that models how "clean" technologies are driving down pollution emissions over time. These technologies allow for improved production efficiencies while simultaneously reducing pollution emissions, therefore we would expect to see the economy growing and pollution shrinking over time.

CHAPTER 3. U.S. STATE-LEVEL CARBON DIOXIDE EMISSIONS: A SPATIAL-TEMPORAL ECONOMETRIC APPROACH OF THE ENVIRONMENTAL KUZNETS CURVE

3.1 Introduction

The debate between economic growth versus environmental degradation is just as relevant today as it was in 1972 with the publication of the classic *Limits to Growth* monograph in which the authors espoused the Malthusian view that the world's ever-dwindling resource base cannot continue to support unfettered economic expansion (Meadows et al., 1972). The relevancy of the debate can be found in the recent 2010 publication of *Eaarth: Making a Life on a Tough New Planet*, in which the author formulates similar arguments to the ―Limits" publication.

The intuition of many environmentalists is that pollution will continue unabated as a country's economy grows through time. An examination of the empirical relationship between economic growth and emissions, however, often reveals different results as evidenced by the environmental Kuznets curve (EKC) hypothesis. Despite a rather robust literature, issues regarding the spatial and temporal dependence within the literature have not been thoroughly addressed. There has been more attention as of late to the temporal dependence within the data,[12] however very little attention has been paid to spatial dependence. Incorrectly

[12] For example, see Stern and Common (2001), Perman and Stern (2003), and Egli (2004).

omitting spatially lagged variables may lead to inefficient parameter estimates and/or invalid hypothesis testing procedure (biased inference).

To address this deficiency within the literature we will examine the relationship between carbon dioxide emissions (as a proxy for atmospheric pollution) and GDP in the 48 contiguous states in the US from 1963-2001. Carbon dioxide accounted for 84% of U.S. greenhouse gas emissions in 2005 and is one of the largest contributors to climate change (Brown et al., 2008). The emissions estimates are based on the combustion of fossil fuels which is one of the main sources of CO_2 emissions in the U.S. According to a U.S. Environmental Protection Agency report, fossil fuel combustion produced 94.1% of the CO_2 emitted in the U.S. in 2008 (U.S. Environmental Protection Agency, 2008). We have reason to believe that that the data are spatially dependent as emissions within a particular state are affected by the economic activity of its neighboring states. Ramirez and Loboguerero (2002) found strong spatial dependence in income levels across 98 separate countries so we have reason to believe that GDP in one state is affected by its neighbors as well. In accounting for this potential misspecification we seek to properly specify the economic growth-CO_2 emission relationship across the 48 contiguous states and verify the inverted-U shaped relationship within the conventional EKC proposal.

The rest of this paper is structured as follows. In the following section we will offer a brief review of the literature. Next, we set up the spatial fixed panel data model. We then provide a description of the data used to estimate this model and present the empirical estimation procedures and results. Finally, we will discuss the empirical findings including potential policy implications and offer suggestions for further research.

3.2 Literature Review

Rupasingha et al. (2004) were some of the first authors to offer a spatial econometric approach to the EKC hypothesis. Specifically, the authors examined the relationship between per capita income and toxic pollutants at the US county-level. With a quadratic specification the authors find the conventional inverted U-shaped relationship; however, with a cubic specification they find that toxic pollution first decreases, but then increases again as income continues to grow over time (this is sometimes referred to in the literature as a N-shaped relationship). These authors' findings are interesting but the economic growth-pollution relationship is only examined in a cross-sectional context leaving out potential dynamic effects.

Maddison (2006) examined the emissions of sulphur dioxide, nitrogen oxides, volatile organic compounds and carbon monoxide across 135 nations. He analyzed the conventional EKC with spatially augmented weighted values of the dependent variables (the pollution emissions) and independent variables (national income and other covariates) to account for potential spatial dependence within the data. The author found that national per capita emissions of sulphur dioxide and nitrogen oxides are heavily influenced by the per capita emissions of neighboring countries. Despite Maddison's (2006) contribution, his analysis is limited to only two years. He took first differences of the data to control for the independent effects (fixed effects) within each country and then analyzed the data as one large cross-section. By observing only two years of data, a rich set of spatial-temporal dynamics are potentially lost which could be reconciled by offering a longitudinal or panel data approach.

Aldy (2005) offers an analysis of the EKC hypothesis applied to carbon dioxide emissions at the state-level in the US. The author used a panel data approach to estimate the economic growth-pollution relationship between per capita CO_2 emissions and per capita income within each state. He asserted that both the CO_2 emissions and income data are non-stationary and therefore he offered a dynamic ordinary least squares (DOLS) approach in addition to the conventional OLS approach. Aldy (2005) found that the estimated inverted-U shaped relationship varied across several different specifications. The author noted that the temporal non-stationarity may yield misleading results and should therefore continue to be explored in the EKC literature. However, he made no mention of the potential spatial dependence within the data.

3.3 Methodological Approach

To control for spatial dependence, temporal dependence, and state-level independent effects we propose a fixed effects estimation procedure as follows. First, however, we need to distinguish between cases in which temporal dependence may or may not be present. If we believe that the emissions data is characterized by temporal dependence, we may consider specifying a dynamic panel data model which includes a lag term of the dependent variable on the RHS. This is a parsimonious way of accounting for persistent effects of past pollution levels on current pollution levels. In this case, we include a lag term of CO_2 emissions because we believe that the underlying economic structure within each state displays persistency along the time dimension. In other words, a state's demand for energy is driven by the economic growth within that state or by the growth of its neighbor. This underlying economic structure drives energy production which in turn drives carbon dioxide emissions within the state or drives emissions of its neighbor. We posit that this underlying economic process is dependent on previous periods. The dynamic panel data model is specified as

$$y_t = \rho y_{t-1} + X_t \beta + \mu_i + \eta_t + u_t, \tag{3.1}$$

where y_t denotes a $(N \times 1)$ vector of U.S. state-level per capita carbon dioxide emissions which are stacked as successive cross-sections over time for $t = 1,\ldots,T$.[13] ρ denotes the scalar coefficient on the time lagged value of CO_2 emissions. X_t is an $(N \times K)$ matrix of the explanatory variables including per capita GDP and per capita GDP squared; therefore, β is $(K \times 1)$ vector of coefficients on the explanatory variables. μ_i denotes the individual (or heterogeneous) effects within each U.S. state and η_t denotes time effects. In the present analysis we treat the individual effect as fixed meaning that we assume that this variable is correlated with the explanatory variables and approximately ―fixed" over time for each state within the sample. This fixed effect may be thought of as state infrastructure, political structure, topography, basic weather patterns, etc. We could estimate μ_i directly by adding a dummy variable for each cross-section and time period and then estimating the equation via ordinary least squares; this is sometimes referred to as the least squares dummy variable estimator (LSDV).[14] If we allow for the fixed effects term to enter into the error term and we

[13] By stacking the data as successive cross-sections we can suppress the cross-sectional index often indicated as $i = 1,\ldots, N$.
[14] The LSDV estimator can be problematic in the presence of large N and T because it requires dummies for each cross section and time period—this sometimes causes problems of multicolinearity.

estimate (1) without controlling for it, then the estimates will result in omitted variable bias. To control for fixed effects without including a variable for the fixed effects term in (1), we could demean the data (fixed effects or within estimator) or take the first difference of the data (first-difference estimator). Econometric theory tells us that the LSDV coefficient estimates are asymptotically equivalent to the fixed effects estimates.

Alternatively, if we are skeptical about the dynamic specification we could specify the model as a standard fixed effects estimation scheme

$$y_t = X_t\beta + \mu_i + \eta_t + u_t, \tag{3.2}$$

where all the variables are the same as (3.1) but we have eliminated the lagged dependent variable on the RHS of (3.2). Again, we can estimate (3.2) by any standard procedure including LSDV, fixed effects, or first-difference estimation.

To complicate the model a little further, we now assume that the underlying economic process driving emissions and income in one state are affected by emissions and income in neighboring states; i.e., spatial dependence. Specifically, we assume a spatial autoregressive error process as follows where the error term u_t is defined as,

$$\begin{aligned} u_t &= \lambda W u_t + \varepsilon_t \\ E(\varepsilon_t) &= 0 \\ E(\varepsilon_t \varepsilon_t^{'}) &= \sigma_\varepsilon^2 I_N . \end{aligned} \tag{3.3}$$

With (3.3) above we can assume that ε_{it} is a white noise process or we can make the stronger assumption that the error terms are i.i.d. for all i and t with mean zero and variance σ_ε^2. I_N is an identity matrix of size N. λ is the coefficient on the spatial autocorrelation term. W denotes an $(N \times N)$ non-negative spatial weight matrix consisting of zeros along the diagonal and elements w_{ij} elsewhere. w_{ij} is measure of the *a priori* strength of the interaction between location *i* (the row of the *W* matrix) and location *j* (the column) (Anselin et al, 2008). In the simplest case the weights matrix is binary with $w_{ij} = 1$ when *i* and *j* are neighbors and $w_{ij} = 0$ otherwise.[15] In the spatial econometrics literature the weights are generally standardized such that the elements in each row sum to one (row standardization).

According to Anselin et al. (2008), the specification of the spatial weights matrix is of great import in applied spatial econometrics. Initially we will consider an alternative weighting specification based on the distance between state centroids. Later will examine the first-order contiguity specification (i.e., a state's emissions are affected by the emissions of states that share a common border). Finally, we assume the weights remain constant over time. Alternative specifications may allow the scalar parameter to vary over time or allow the weights to vary and the parameter to remain constant. Such specifications would only complicate the analysis, so to keep the empirical approach tractable we assume constant weights across time.

To see how the assumption of spatial autoregressive errors affects (3.1) we can rewrite (3.3) as,

$$\begin{aligned} (I_N - \lambda W)u_t &= \varepsilon_t \\ u_t &= (I_N - \lambda W)^{-1}\varepsilon_t. \end{aligned} \tag{3.4}$$

We can now substitute (3.4) into (3.1) or (3.2) and rewrite some terms to derive,

$$y_t = \rho y_{t-1} + X_t\beta + \mu_i + (I_N - \lambda W)^{-1}\varepsilon_t. \tag{3.5}$$

[15] Hence the zeros along the diagonal since a state cannot be a neighbor to itself.

From an econometrics perspective the issue with estimating (3.5) is a problem of efficiency. If one estimates equation (3.1) or (3.2) without taking the spatial effects into account, then a standard OLS regression will yield downwardly biased standard errors. In other words, the term $(I_N - \lambda W)^{-1}$ will cause an increase in the variance of ε_t. This problem of inefficiency can be accounted for through instrumentation (IV or GMM) or by specifying a complete distribution model (maximum likelihood).

Elhorst (2005) developed a complicated unconditional maximum likelihood estimator for dynamic, spatial panel data in which he takes the first difference of the data to eliminate the fixed effects term. The problem with Elhorst's procedure is that it requires the awkward assumptions about the initial conditions for y_0 and X_0. Bond (2002) criticizes this procedure by stating that the distributions of both y and X for t = 2, 3, …, T could depend in a ―non-negligible" way on what is assumed about the initial condition (especially if T is short).

Another potential strategy for estimating (3.1) – (3.3) is to perform the conditional maximum likelihood (CML) estimation procedure. Hsaio et al. (2002) show that with dynamic panels the LSDV estimator is asymptotically equivalent as the CML estimator. LSDV can be biased or inconsistent so this calls into question the appropriateness of the CML procedure. Further, Hsaio et al. (2002) show that the LSDV or CML estimators are inconsistent if T is finite and N tends toward infinity (i.e., the incidental parameters problem).[16] Anselin et al. (2008) cast further doubt on this estimation procedure as they posit that LSDV is generally not recommended in spatial models.

[16] Alternatively, the LSDV and CML estimators are consistent if T tends toward infinity, although Hsaio et al. (2002) do not proscribe a length of T to maintain consistency.

A third possible estimator for (3.1) – (3.3) is the Generalized Method of Moments (GMM). Roodman (2006) though suggests only using GMM with ―small T, large N" panels because the dynamic panel bias (Nickel 1981) becomes insignificant as T grows and he suggests that a more straightforward fixed effects estimator is more appropriate. Elhorst (2003) offers a fixed effects (FE) estimator for panel data but Anselin, et al. (2008) argue that it is biased.[17]

Given that our panel consists of $T = 39$, the asymptotics of CML estimator is questionable and following Roodman's (2006) advice the GMM may not be appropriate. Elhorst's (2005) unconditional ML estimator is attractive but too complicated, and since Elhorst's (2003) FE estimator is biased we propose the following iterative Spatial Fixed Effects (SFE) estimator which is efficient, asymptotically normal and robust to heteroskedasticity and serial correlation. In principal the SFE estimator is also far simpler to compute than GMM, Elhorst's unconditional ML, and Elhorst's FE estimator. To begin, we rewrite (3.1) and (3.3) by dropping the time subscript for ease of exposition (again, the variables are still stacked as successive cross-sections over time).

$$y = Z\gamma + (I_T \otimes \mu) + u \tag{3.6}$$

$$u = \lambda W u + \varepsilon, \tag{3.7}$$

where $Z = (y_{-1}\ \ X)$, $\gamma = (\rho\ \ \beta)'$, and the weighting matrix $W = (I_T \otimes W_N)$.[18] I_t is an identity matrix of dimensions $(T\ x\ T)$ and the subscript N on W indicates that it is

[17] See the Appendix below for an explanation for why Elhorst's FE estimator is biased.
[18] If we specify the standard fixed effects then the lagged dependent variable would be eliminated from Z.

of dimensions (*N x N*). Following Anselin et al. (2008) we define the "within" transformation operator as[19]

$$Q = I_{NT} - \left(\frac{\iota_T \iota_T^{'}}{T} \otimes I_N \right), \qquad (3.8)$$

where I_{NT} is an identity matrix of (*NT x NT*) and ι_T is a vector of ones of length *T*. We can multiply the within transformation operator through (5) and (6) to eliminate the fixed effects term, μ, as follows

$$Qy = QZ\gamma + Qu \qquad (3.9)$$

$$Qu = \lambda WQu + Q\varepsilon\,. \qquad (3.10)$$

Following Ord (1975) we can estimate γ by least squares relying upon the assumption that if *T* is large then the dynamic panel bias becomes insignificant. Ord (1975) states that if the spatial autocorrelation parameter (λ) is unknown, even a constrained least squares procedure produces inconsistent estimators. He defines an iterative procedure that we extend here to a panel data model:

1. Compute the GLS residuals from (3.9) to derive $Q\tilde{u}$ [20]
2. Estimate $\tilde{\lambda}$ from $Q\tilde{u} = \lambda WQ\tilde{u} + Q\varepsilon$ by using the Newton-Raphson Method to derive $\tilde{\lambda}$.
3. Construct new variables $\ddot{y} = (I_{NT} - \tilde{\lambda}W)Qy$ and $\ddot{Z} = (I_{NT} - \tilde{\lambda}W)Qz$
4. Apply OLS for $\ddot{y}$ on $\ddot{Z}$ to yield $\hat{\gamma}$.
5. Construct the new residuals $\hat{\ddot{u}} = \ddot{y} - \ddot{Z}\hat{\gamma}$ and return to Step 2 to calculate $\hat{\lambda}$.
6. Construct the robust covariance for $\hat{\gamma}$ by calculating $\hat{A} = \frac{N}{N-K}(\ddot{Z}'\hat{\ddot{u}}\hat{\ddot{u}}'\ddot{Z})$.[21]

[19] By within transformation this means that each cross-section is demeaned "within" its own section; e.g., all the CO_2 emissions in Wisconsin will be demeaned based upon the mean of emissions from Wisconsin. The reader should note that the demeaning operator is slightly different from the operator within the traditional panel data models because the data is organized differently.

[20] Notice we use the GLS procedure because Q^{-1} does not exist since it is idempotent. Instead we use the pseudo-inverse (or Moore-Penrose Inverse) as defined in Hsiao (2003).

[21] $\hat{A}$ is often referred to as the meat of the sandwich from the "sandwich estimator". The term *(N / N – K)* is a degrees of freedom correction since $\hat{\ddot{u}}$ is biased.

One may notice that this algorithm is very similar to the Cochrane-Orcutt estimation procedure (Cochrane and Orcutt, 1949). Conveniently this same iterated procedure can be performed with a panel first-difference (FD) estimator. We refer to this procedure as the iterated spatial first-difference (SFD) estimator. The algorithm is almost identical to the SFE procedure (for the specific algorithm, please refer to the Appendix). Like the SFE, depending on certain assumptions the SFD estimator is consistent, asymptotically normal, and contains standard errors robust to heteroskedasticity and serial correlation. In principal one would repeat steps 1 through 5 multiple times until the parameter estimates do not change and then finally perform step 6.

Since the spatial error coefficient, λ, is numerically approximated via the Newton-Raphson algorithm we do not estimate its standard error. Without the standard error estimate we cannot calculate the usual *t*-statistic to determine if the coefficient is statistically significant. Its significance is important in determining whether our spatial error process is a correct specification. However, we can somewhat get around this problem by using a Lagrange Multiplier (LM) test to determine if there is spatial dependence within the data. We use LM test developed by Burridge (1980) to determine if there is significant spatial dependence within the panel. The LM test is as follows

$$LM_E = \frac{[Q\tilde{u}'(I_T \otimes W_N)Q\tilde{u} / (Q\tilde{u}'Q\tilde{u} / NT)]^2}{tr[(I_T \otimes W_N^2) + (I_T \otimes W_N' W_N)]}, \tag{3.11}$$

where $Q\tilde{u}$ are the derived residuals from Step 1 of the algorithm above and tr indicates the trace of the elements in the denominator. Burridge's (1980) LM test is distributed as a chi-square with one degree of freedom. If we find statistical evidence from this LM test that the data is characterized by spatial dependence then we have reason to believe that our spatial error process specification is correct.

3.4 Data Description

3.4.1 CO_2 Emissions

The CO_2 emissions data were obtained from the Carbon Dioxide Information Analysis Center (CDIAC) within the U.S. Department of Energy (Blasing et al., 2004). CDIAC estimates the emissions by multiplying state-level coal, petroleum, and natural gas consumption by their respective thermal conversion factors. This gives us the ability to calculate the amount of heat energy derived from fuel combustion. Therefore, this dataset represents estimates of CO_2 emissions and not actual concentrations (or actual atmospheric pollution), which is somewhat problematic as actual concentration data would be more desirable for testing spatial spillovers within the pollutant itself. The reason for using this particular dataset, however is that it offers emissions estimates dating back to the 1960, well before the establishment of the Environmental Protection Agency (EPA) and stronger enforcement of the U.S. Clean Air Act. Most CO_2 emissions data are only available after the establishment of the EPA (i.e., from the 1970s onward).[22] Therefore, we use this dataset because it offers observations before the establishment (or enforcement)

[22] We believe that the establishment of the EPA coupled with stronger enforcement of the Clean Air Act could potentially bias the shape of the pollution-income relationship, especially if observed emissions are collected after the 1970's which is often the case in pollution emissions data.

of state and national pollution emission regulations. CO_2 emissions are offered in per capita terms by dividing total state-level emissions by the state population in a given year.

3.4.2 GDP

The GDP data was obtained from the Bureau of Economic Analysis (BEA) within the U.S. Department of Commerce (Bureau of Economic Analysis, 2010). The BEA offers annual state-level GDP estimates from 1963 to the near present. The estimates are based on per capita nominal GDP by state. The estimates were converted to real dollars by using the BEA's implicit price deflator for GDP. Following the traditional EKC hypothesis, GDP is expected to have an inverted U-shaped relationship with CO_2 emissions; in other words, a quadratic polynomial of GDP will be specified in which the expected sign on the GDP term is positive while the expected sign on the squared term is negative. To test this specification the polynomial can be extended to higher powers to determine if the leading term is statistically significant. For example, if a cubed GDP term is positive and statistically significant, the implication is that the economic growth-pollution relationship is N-shaped—i.e., a relationship that is characterized by an initial increase in pollution, followed by a decrease, and then an increase once again as economic growth continues over time. We hypothesize that the quadratic relationship is the correct specification.

3.4.3 CDD and HDD

Cooling Degree Days (CDD) and Heating Degree Days (HDD) data were obtained from the National Climate Data Center within the National Oceanic and

Atmospheric Administration (National Climate Data Center, 2010). The data are offered in a state population-weighted format consistent with the rest of the data in the study. CDD (or HDD) is a unit of measure to relate the day's temperature to the energy demand of cooling (or heating) at a residence or place of business—it is calculated by subtracting 65 degrees Fahrenheit from the day's average temperature (Swanson, 2005). Residential energy consumption has been found to be highly correlated with CDD and HDD (Diaz and Quayle, 1980). Since the CO_2 emissions are estimated from energy consumption, the CDD and HDD data as quantitative indices should capture much of the year-to-year variation in energy consumption. CDD and HDD are expected to be positively related to CO_2 emissions as cooler (or hotter) days would induce households or businesses to demand higher amounts of energy for cooling (or heating) a residence or place of business.

3.4.4 Energy Production

The energy production data were obtained from the Energy Information Administration within the U.S. Department of Energy (Energy Information Administration, 2008). The energy production data represent state-level annual production of coal, crude oil, natural gas, and renewable energies. The data are represented in physical units: short tons, barrels, and cubic feet. The production data was converted to a population-weighted format by dividing today physical units by the state's annual population estimate. Due to data limitations, the natural gas and renewable energy production measures were dropped from the analysis. The coal and oil production measures are left in levels as several of the measures contain zeros; i.e., not all states produce coal or oil. State-level production is expected to be positively related to CO_2 emissions as an increased supply in energy may make consumption of the energy more readily available for the state. For example, if a state produces coal then it is expected that that state will keep some in reserve to use in energy production within state.

3.4.4 Population

Annual state population data were obtained from the U.S. Bureau of Census (Population Estimates). These population estimates represent the total number of people of all ages within a particular state.

3.5 Empirical Estimation and Results

3.5.1 Panel Unit Root Test

Before examining the regression results it would be an informative exercise to briefly determine if the main variables (CO_2 and *GDP*) within the dataset are characterized by a unit root; i.e., the variables are non-stationary. According to Barbieri (2006) there are basically two types of panel unit root tests: the first type assumes cross-sectional *independence*, whereas the second type assumes cross-sectional *dependence*. Consistent with our spatial spillovers argument we have reason to believe that the data would be characterized by cross-sectional dependence. In other words, we believe that the economic activity within one state affects the economic activity of its neighbor or trading partner; i.e., there is dependence across the cross sections. In order to determine if there is cross-sectional independence we employ the parametric testing procedure proposed by Pesaran (2004). Using Pesaran's test (not shown) we reject the null hypothesis (at a one percent significance level) which offers evidence against the null hypothesis of cross-sectional independence. Thus, it would seem that the second type of panel unit root test would be more appropriate. Nevertheless, we offer the test results for both types of panel unit root tests in Table 3.1 below.

The test in second column of Table 3.1 is based upon the work of Im, Pesaran, Shin (2003) (Ipshin test) which assumes cross-sectional independence. The test in the third column is based upon Pesaran (2005) which assumes cross-sectional dependence; the “CADF” indicates a cross-sectional augmented Dickey-Fuller test. The null hypothesis of both tests assumes that the series is non-stationary (i.e., is characterized by a unit root).[23] The Ipshin test implies that CO_2 and *GDP* are stationary when just the lag term is included, but are non-stationary when the trend is included. The Pesaran CADF test implies that CO_2 is non-stationary for both specifications, and *GDP* is non-stationary if two lags and a trend are included. Thus, there seems to be good evidence that CO_2 emissions are characterized by a unit root. The results for *GDP* are less certain, but intuition would lead one to believe that *GDP* is characterized by a unit root as well; in other words, preceding state-level GDP should have a significant effect on current state-level GDP. Lastly, taking the difference of the variables (represented by the sixth and seventh rows) implies stationarity with the exception of *GDP*. The Pesaran test implies stationarity for *GDP* when two differences were taken (not shown).

[23] The results of both tests were robust to tests with higher lags of variables, so we specify two lags out of convention that both variables are offered annually.

Table 3.1. Panel Unit-Root Tests

Variable	Im, Pesaran, Shin Test	Pesaran CADF Test
CO_2 with two lags	-1.671 (0.070)	-1.744 (0.577)
CO_2 with two lags and trend	-1.969 (0.893)	-2.045 (0.990)
GDP with two lags	-1.764 (0.014)	-2.010 (0.038)
GDP with two lags and trend	-2.144 (0.420)	-2.456 (0.181)
D.CO_2 with two lags and trend	-3.775 (0.000)	-3.618 (0.000)
D.GDP with two lags and trend	-2.944 (0.000)	-2.399 (0.320)
Notes: The top number represents the t-bar value and the bottom number represents the p-value. The D.* indicates a difference of variable was taken.		

If CO_2 is characterized by a unit root and the rest of the variables are stationary then the dynamic spatial fixed effects estimator may be the most appropriate estimation scheme because the dynamic specification controls for the non-stationarity within the dependent variable. If CO_2 and *GDP* are both first-order difference stationary then the spatial first-difference estimator may be the most appropriate estimation scheme because differencing the data renders both variables stationary; there is marginal evidence in Table 3.1 that both are first-order difference stationary. Since the test results of the Ipshin and Pesaran CADF are not conclusive we will estimate all four types of our proposed estimator; i.e., spatial fixed effects, spatial first differences, dynamic spatial fixed effects, and dynamic first differences. Offering the results for all four types presents a sensitivity analysis across our proposed estimation schemes.

3.5.2. Estimation Results

Following the traditional EKC hypothesis with the quadratic specification, we define the spatial-temporal economic growth-pollution relationship as

$$\begin{aligned} \ln(y_{it}) &= \alpha + \rho y_{it-1} + \beta_1 \ln(GDP_{it}) + \beta_2 \ln(GDP_{it})^2 + \beta_3 \ln(CDD_{it}) \\ &\quad + \beta_4 \ln(HDD_{it}) + \beta_5 prod_{it} + \mu_i + \eta_t + u_{it} \end{aligned} \tag{3.12}$$

$$i = 1,\ldots,N;\ t = 1,\ldots,T$$

where y_{it} is real per capita CO_2 emissions in a U.S. state, y_{t-1} denotes its lagged value, and α denotes the intercept term. GDP_{it} is real per capita state-level GDP, and GDP_{it}^2 is the square of the same term. CDD_{it} is per capita cooling degree days, whereas HDD_{it} is per capita heating degree days. The term $prod_{it}$ denotes per capita state-level annual production of coal and crude oil. We assume fixed state-specific effects, μ_i. Time effects are denoted by η_t. The state-specific effects capture heterogeneous elements within each state that may affect CO_2 emission levels. All variables with the exception of the intercept terms and energy production are expressed in natural logarithms out of convention.[24] Once again, we can estimate (3.12) as the standard fixed effects by removing the lagged dependent variable from the RHS. The observations in (3.12) are available from 1963-2001 so that $T = 39$. The observations in (3.12) constitute the 48 contiguous states in the U.S. excluding the District of Columbia so that $N = 48$.

For ease of exposition, the variables are stacked as successive cross-sections over time for $t = 1,\ldots,T$. Next we place the explanatory variables into an $(N \times K)$ matrix X_t and place their corresponding coefficients into a $(K \times 1)$ matrix β and rewrite (3.12) as

[24] Production is not expressed in natural logs because several states had zero values for coal or oil produced which is undefined when converted to natural logs.

$$y_t = \rho y_{t-1} + X_t \beta + \mu_i + \eta_t + u_t. \tag{3.13}$$

As in (3.3) above we define the error term as

$$u_t = \lambda W u_t + \varepsilon_t$$
$$E(\varepsilon_t) = 0$$
$$E(\varepsilon_t \varepsilon_t') = \sigma_\varepsilon^2 I_N.$$

Given the assumption of the error term in (3.3) we can rewrite (3.13) as

$$y_t = \rho y_{t-1} + X_t \beta + \mu_i + \eta_t + (I_N - \lambda W)^{-1} \varepsilon_t \tag{3.14}$$

The regression equation in (3.14) has a spatial autoregressive process incorporated in the error term with a spatial weight matrix specified as the inverse distance from the state centroids (we will also consider a spatial weight matrix specified as a normalized binary contiguity matrix later in the study).

For a sensitivity analysis we compare the iterated SFE and SFD estimators to the other estimation schemes discussed in the Methodological Approach; i.e., LSDV, Elhorst's FE, Elhorst's unconditional maximum likelihood estimator (UMLE). Table 3.2 reports the estimation results based on the complete sample of 1872 observations (or 1824 observations in terms of the SFD estimator). The SFE and SFD procedures are dynamic (specified as ―Dynamic" in the table) when the lagged dependent variable is included in the RHS and standard otherwise. As we noted in the Methodological Approach section above this estimation procedure yields efficient estimates of the growth-pollution relationship. The second column indicates the least squares dummy variable (LSDV) estimates.[25] The LSDV estimator may suffer from multicolinearity; nevertheless, the LSDV estimates are used as a baseline of

[25] The LSDV estimates are equivalent to the parameter estimates from Step 1 of the iterated SFE as predicted by econometric theory.

comparison against the other estimation schemes. Columns three and four report the results for the spatial fixed effects estimator and the fixed effects, unconditional maximum likelihood estimator (Elhorst, 2005) respectively. The fifth and sixth columns represent the standard spatial fixed effects and spatial first-difference estimators outlined in this chapter. Finally, columns seven and eight represent the dynamic procedures. Unlike the other estimation schemes the LSDV, Elhorst's FE, SFE, and SFD estimators do not account for a lagged dependent variable or spatial error autocorrelation which explains the absence of estimates for $CO_{2,t-1}$and λ (the spatial autocorrelation parameter) in its column.

Table 3.2. Estimation Results for the Economic Growth-CO_2 Emissions Relationship (Quadratic Specification) with Distance-Based Spatial Weighting Matrix

	Model Types						
Explanatory Variables	**LSDV**	**Elhorst FE**	**Dynamic Elhorst FE**	**SFE**	**SFD**	**Dynamic SFE**	**Dynamic SFD**
$CO_{2,t-1}$	N/A	N/A	0.9706*** (185.852)	N/A	N/A	0.1182*** (3.5021)	0.0036 (0.7865)
GDP	12.6768*** (18.4822)	15.325*** (10.8307)	1.564*** (4.7597)	12.5123*** (4.4893)	5.6676** (2.2663)	9.7176*** (5.1727)	5.3303* (1.9810)
GDP^2	-0.6196*** (-18.4207)	- 0.7666*** (-10.992)	-0.078*** (-4.8157)	-0.6112*** (-4.5091)	-0.2685** (-2.1535)	- 0.4777*** (-5.2082)	-0.2522* (-1.8834)
CDD	-0.0179 (-0.8664)	0.3222*** (23.0336)	0.0212*** (5.9369)	-0.0175 (-0.2104)	0.0131 (1.0407)	0.0109 (0.2132)	0.0137 (1.0273)
HDD	0.0692 (1.3415)	0.3497*** (16.5263)	0.0277*** (5.4346)	0.0618 (0.3752)	0.1024 (3.4171)	0.1052 (1.0375)	0.1045*** (3.3073)
Coal	0.0015*** (10.1853)	0.0037*** (26.4352)	0.0001*** (2.672)	0.0016* (1.6760)	0.0011*** (1.2924)	0.0015** (2.6017)	0.0011 (1.2189)
Oil	-0.0008*** (-3.1082)	0.0036*** (25.4736)	0.0003*** (9.0636)	-0.0006 (-0.4934)	0.0005 (0.5286)	-0.0001 (-0.1490)	0.0005 (0.5182)
λ	N/A	0.056* (1.7845)	0.02 (0.63)	-0.0150	0.0071	0.0324	0.0075
R^2	0.9402	0.6028	0.9796	0.6028	0.6019	0.7347	0.7347
Adjusted R^2	0.9371	0.5894	0.9789	0.5932	0.5934	0.7291	0.7289
Robust SE	No	No	No	Yes	Yes	Yes	Yes

Notes: The numbers in the parentheses denote t-statistics. The superscripts ―***", ―**", ―*" denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate. Parentheses for spatial autocorrelation coefficient (λ) represent chi-squared statistics determined by Burridge's LM test.

The LSDV estimates imply the usual inverted-U shaped relationship of the EKC hypothesis and both indicators of income are statistically significant. The positive sign on the HDD is consistent with expectations that an average increase in HDD will increase the heating of buildings which in turn will require additional combustion of fossil fuels which then raises CO_2 emissions. The negative sign on oil production is not necessarily consistent with expectations as an increase in oil production within a state may elevate CO_2 emissions as the burning of that fossil fuel would be more readily available within that particular state for the production of energy. However, it could be that the states producing higher levels of oil are exporting a significant portion of their oil to other states or abroad. As expected, coal production is positive and statistically significant at the five percent level of significance.

Looking across the different estimation schemes, the estimates for the lag of CO_2 emissions are highly statistically significant with the exception of the Dynamic SFD estimate.[26] In the case of Elhorst's Dynamic FE estimate we already know that it is inefficient and given Bond's (2002) argument about UMLE, we know that it depends in an unequivocal way on the assumptions about the initial conditions. The SFE and SFD procedures find much lower estimates for the lag of CO_2 that is closer to the LSDV estimate. According to Wooldridge (2002) the choice between a standard FE and FD estimator depends on the assumptions of the idiosyncratic error term, ε. He claims that FE is more appropriate when ε_{it} are serially uncorrelated while the FD is more appropriate when ε_{it} follows a random walk. However, Wooldridge (2002) claims that the true estimates probably lie somewhere in between the FE and FD.

Since the underlying demand for energy is driving CO_2 emissions we have reason to believe that it is non-stationary; in other words, we expect a degree of persistence along the time dimension of CO_2 emissions. Our panel unit root tests in

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[26] If there is a high degree of persistence within CO_2 emissions (i.e., $\rho \cong 1$) then this dynamic spatial estimation scheme may inherently yield a difference stationary process for CO_2 emissions. To see this rewrite (3.13) as

$$\Delta y_t = (\rho - 1) y_{t-1} + X_t \beta + \mu_i + u_t,$$

so if the true value of ρ is close to one (persistence) then the lagged dependent variable is approximately equal to zero and the dependent variable is first-order difference stationary. If this is the case then the Dynamic SFD procedure may over-difference the CO_2 series which may bias the estimates. The results of the panel unit root test in Table 3.1 seem to imply that CO_2 data are first-order difference stationary, so the Dynamic SFD estimator may indeed yield biased results.

Table 3.1 seem to corroborate this belief. Therefore, the SFD may be a better estimation scheme in this case; i.e., the SFD does not over-difference the data.

In general the economic growth terms (income and income squared) are statistically significant across the estimates and follow the traditional inverse-U shaped relationship espoused by the EKC hypothesis. The estimates for income and income squared with the SFD procedure are slightly lower than most of the other schemes (with the exception of the UMLE). If income is characterized by a non-stationary process (which is usually found in the literature) then first differencing the procedure (as done with the SFD approach) may yield a difference-stationary process—in which case the SFD estimates may be more appropriate.

Coal production was found to be statistically significant across all the estimation schemes with the exception of the Elhorst's UMLE procedure. All signs are positive which is consistent with expectations as we believe that an increase in coal production would increase its burning as a fossil fuel which in turn would increase CO_2 emissions. The effect is relatively small, but it is robust across the estimators; e.g., in the case of the SFE estimate the interpretation is that a 100% increase in coal production yields a 0.1% increase in CO_2 emissions.

The spatial autocorrelation coefficient (λ) was found to be statistically significant with two of the three procedures. This significance indicates that neighboring spatial effects influence local CO_2 emissions. One will notice that estimates for the variance of this coefficient are absent from the SFE, SFD, Dynamic SFE, and Dynamic SFD procedures. This unfortunately is one of the drawbacks of using these two procedures. Recall that we used a Newton-Raphson algorithm to numerically approximate this coefficient. Since the other procedures statistically estimate this coefficient, they are able to generate its first and second moments. To determine if the spatial error specification appears to be correct we use the LM test outlined in the Methodological Approach section of the chapter. Our results for Burridge's (1980) LM test statistic are listed in Table 3.3 below. The results for this LM test give us mixed results as to whether our spatial error specification is correct and the SFE and SFD procedures (or their dynamic counterparts) are appropriate. The fixed effects procedures yield highly significant results whereas the first-differencing procedures yield insignificant results.

Table 3.3. Burridge LM Test Results

	Model Types			
Explanatory Variables	**SFE**	**SFD**	**Dynamic SFE**	**Dynamic SFD**
	45.8233 (0.0000)	0.4788 (0.4538)	124.6573 (0.0000)	0.4731 (0.4578)
The top number is the chi-squared statistic. The bottom number is the p-value of the statistic.				

The estimation results with the first-order continguity spatial weighting matrix are listed in Table A.3.1 in the Appendix. It is worth noting that there no real tangible differences between the two weighting mechanisms; i.e., signs are similar, the same estimates are statistically significant, and R^2 values are very similar. The only difference is that the estimates appear to be slightly smaller in general with the first-order continguity—this could stem from the fact that the nearest neighbor spatial weighting matrix may be too simple of a specification. In other words, the nearest neighbor specification implies that economic activity only takes place between neighboring states. Most importantly though the purported inverse-U shaped relationship still seems to hold even with a different weighting mechanism.

Lastly, we follow up with Aldy's (2005) analysis where he found statistically significant results for both a quadratic and cubic specification of income. If we find statistically significant results for a cubic specification then it may imply that the pollution-income relationship is following an N-shaped path; i.e., pollution initially rises, tapers off some, and then rises again.[27] This N-shaped relationship implies that CO_2 emissions are not decreasing but increasing with income over time—this refutes the inverted U-shaped relationship.[28]

The results for the cubic specification estimates are presented in Table A.3.1 in the Appendix. The lagged CO_2 estimate remains significant with this parametric specification; however, the income terms become insignificant for almost all of the estimation schemes. For the SFE estimator only GDP is significant at a ten percent level but the other GDP terms become insignificant. With the SFD estimation scheme all the income terms are significant at a ten percent level, but the signs do not indicate an N-shaped relationship. Rather, the signs indicate that emissions initially fall then rise and then fall once again (i.e., an inverted-N relationship). Thus, there does not appear to be ample evidence to support growing CO_2 emissions over time with income which seems to offer support in favor of the traditional EKC inverted-U shaped relationship.

[27] This would imply that the sign on GDP is positive, negative for GDP^2, and positive for GDP^3.

[28] Although, Carson (2010) argues that a significant cubic specification may come from the fact that the economic growth-pollution relationship has a relatively flat right tail which the cubic specification may fit better than the quadratic specification.

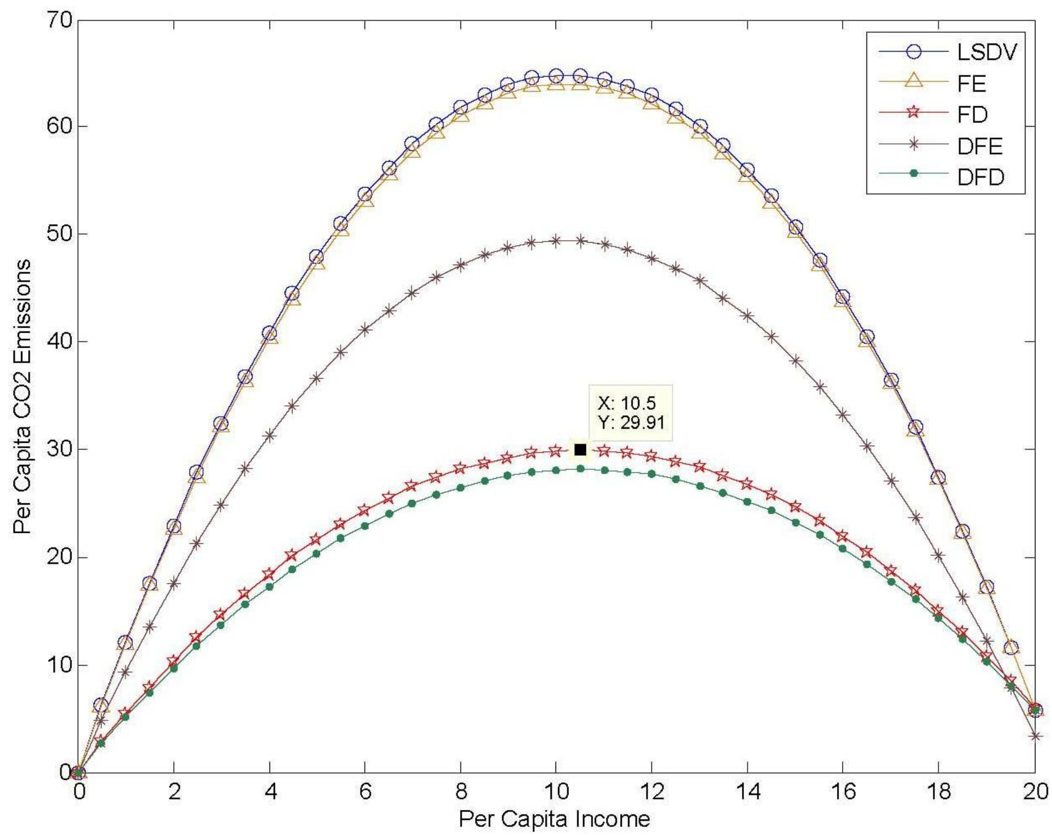
Lastly, we project the economic growth-pollution relationship based upon our estimation results derived from Table 3.2 above. LSDV denotes least squares dummy variable, SFE denotes spatial fixed effects, SFD denotes spatial first differencing, Dynamic SFE denotes dynamic spatial fixed effects, and Dynamic SFD denotes dynamic spatial first differencing. Interestingly, all the different estimation schemes seem to yield estimated results that peak around the natural log of 10.5 of per-capita income (i.e., approximately $36,000). These similar peaks occur because the different estimation schemes are unbiased. As outlined above, the LSDV estimates are larger than the other estimators probably because of multicolinearity and it does not control for spatial and temporal dependence. Asymptotically, the SFE estimates should be similar to the LSDV estimates which are displayed below, but the SFE estimates are transformed to control for spatial dependence so its estimates are slightly smaller than the LSDV estimates. The Dynamic SFE controls for temporal dependence in the dependent variable and spatial dependence for all the variables so its estimates are smaller than the SFE estimates.

The SFD estimates control for spatial and temporal dependence, and therefore should have some the smallest estimates which the figure below seems to corroborate (assuming the data are first-difference stationary). The Dynamic SFD estimates are the smallest because the data is differenced twice (and these estimates control for spatial dependence), but we question these results because the Dynamic SFD scheme may be over-differencing the data.[29] Therefore, based upon the results and Figure

[29] This result could possibly be correct if CO_2 is second-order difference stationary.

3.1, it would seem that in this case the SFD estimator probably offers the best explanation of the economic growth-pollution relationship.

Figure 3.1. Projected Plots Based Upon Estimation Results



3.6 Implications and Conclusions

Issues associated with temporal and spatial dependence have largely been ignored in the Environmental Kuznets Curve hypothesis. In this paper, we introduced a spatial panel data model approach to account for spatial dependence that is expected to be found within the underlying economic activity that drives CO_2 emissions and state-level income. We used iterated spatial fixed effects and spatial first difference estimator approaches to estimate this spatial-temporal economic growth-pollution relationship. Unlike past estimators these iterated procedures are in principal much easier to implement and yield asymptotically efficient estimates. Additionally, this estimation procedure contributes to the literature by offering standard errors that are robust to heteroskedasticity and serial correlation. Based on the empirical results, we believe that we have relatively compelling evidence that this spatial panel approach tells a consistent story with respect to expected signs, magnitudes, significant levels, and spatial autocorrelation.

Based upon our empirical results we find evidence that is consistent with the traditional EKC hypothesized inverted-U shaped relationship between economic growth indicators (income) and CO_2 emissions as a proxy for atmospheric pollution. This inverted-U shaped relationship is found even after controlling for spatial dependence within the data, which seems to offer further support to the purported EKC hypothesis.[30] Unlike past literature, we also find fairly consistent evidence of spatial autocorrelation within the data—these findings imply that CO_2 pollution emissions are not necessarily a local issue.[31] In other words, a neighboring state's demand for energy may be driving pollution emissions locally. For example, a state generates electricity locally but then exports the electricity to a neighboring state—if the neighboring state is experiencing economic growth then it may demand more electricity. If the exporting state generates the electricity through the combustion of coal, then it has a dirtier atmosphere because its neighbor demand for energy has increased. CO_2 emissions then are not a local issue. This insight has tremendous policy implications both at the federal and state level.

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[30] Additionally, it could be argued that the SFD scheme potentially controls for temporal non-stationarity if indeed the first-difference procedure yields difference-stationary processes.
[31] We are not making an argument about CO_2 concentrations in the atmosphere, but rather CO_2 emissions because our data are estimates of emissions based upon the combustion of fossil fuels.

According to the recent Copenhagen Treaty, the U.S. is to reduce CO_2 pollution emissions by 17% below 2005 levels by 2020. If we are to reach these reduction levels, then the states must adopt regional reduction plans as evidenced by the significant spatial autocorrelation found in this study. The spatial dependence found within in study implies that transboundary pollution associated with CO_2 emissions is potentially a real issue. This regional pollution problem is further complicated by the fact that some states produce fossil fuels while others do not. For example, the state of Georgia's electricity generation and consumption is among the highest in the U.S. despite there being no coal production in the state (coal supplies about half of the electricity output in the state), which means the coal is imported from other states (U.S. Energy Information Administration, 2010). The regional plans to reduce emissions then must inevitably involve energy trading as well as regional regulations to reduce emissions. It is possible that neighboring states may develop cooperative initiatives to reduce emissions which include energy trading and production. The bottom line is that these regulations or initiatives need to start being developed soon if we are to reduce CO_2 emissions to remain compliant with the 2009 Copenhagen Treaty.

3.6.1 Limitations

One of the drawbacks of the iterated SFE and SFD procedures are that the variance of the spatial autocorrelation parameter, λ, is not estimated because the parameter is determined by a numerical approximation instead of estimated statistically. With a statistical procedure the first and second moments of the autocorrelation parameter can easily be estimated. Despite our lack of variance estimates, we believe the other spatial estimation schemes present evidence that emissions are influenced by spatial effects, and therefore the lack of variance estimates does not undermine the results based upon the SFE and SFD procedures.

We faced some significant limitations while conducting this analysis. One of the major obstacles is that there are few if any statistical programs that compute spatial panel data estimates. The analysis for this work was conducted entirely in Matlab. The SFE and SFD procedures were written by authors. The code for the FE and UMLE estimators was obtained from Elhorst's (2010) personal website. Stata is working on a written procedure for Cliff-Ord spatial models, but the procedure has not been made available to the public as of yet. Piras (2009) has developed a library in R for estimating spatial panel data models, but does not offer a procedure for dynamic spatial data models.

Finally, the model may be greatly improved by specifying a spatial heterogeneous parameter model as opposed to the homogeneous model we have specified in this analysis. By homogeneity we are implicitly assuming that each state has the same economic growth-pollution relationship (including the shape) on average across time. As our analysis is restricted to the contiguous 48 states this may not be so problematic, but should the analysis be extended to an international study, then the homogeneity assumption may prove more problematic. Of course, implementing a heterogeneous panel model is already problematic because of the incidental parameters problem, so extending the panel to include heterogeneous spatial dependence may prove to be very difficult. A clustering estimation scheme may be more appropriate for considerations of spatial heterogeneity.

3.7 Appendix

3.7.1 Bias of Elhorst (2003) Fixed Effects Estimator

To demonstrate how Elhorst's FE estimator is biased we follow equations (8) from above:

$$Qy = Qz\gamma + Qu \tag{A.3.1}$$

$$Qu = \lambda WQu + Q\varepsilon \tag{A.3.2}$$

where we used the demeaning operator to remove the fixed effect. We can now rewrite (A.3.1) and (A.3.2) as

$$(I_{NT} - \lambda W)Qy = (I_{NT} - \lambda W)z\gamma + Q\varepsilon \tag{A.3.3}$$

Elhorst (2003) incorrectly assumes that

$$E(\varepsilon\varepsilon') = \sigma^2 I_{NT}\,, \tag{A.3.4}$$

when in actual fact

$$E(\varepsilon\varepsilon') = \sigma^2 Q.^{32} \tag{A.3.5}$$

Elhorst (2003) then constructs a maximum likelihood estimation scheme based upon assumption (A.3.4). If one tries to correct for assumption in (A.3.4) by replacing it with (A.3.5) then the MLE procedure is no longer appropriate because it requires the inverse of Q to be calculated. Since Q is idempotent its inverse does not exist.[33] Therefore, the Elhorst (2003) FE estimator is biased.

3.7.2 Iterative Spatial First Difference Estimation Algorithm

Instead of using the demeaning operator to get rid of the fixed effects, one can alternatively first difference the data for (5) and (6) to obtain:

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[32] The reader should note that since Q is idempotent so $Q'Q = Q$.
[33] The identity matrix is the only idempotent matrix that has an inverse that exists.

$$\Delta y = \Delta z\gamma + \Delta u \tag{A.3.6}$$

$$\Delta u = \lambda W \Delta u + \Delta\varepsilon \tag{A.3.7}$$

Based on first differencing the data, the new algorithm is as follows:

1. Compute the OLS residuals from (A.1) to derive $\Delta\tilde{u}$
2. Estimate λ from $\Delta\tilde{u} = \lambda W \Delta\tilde{u} + \Delta\varepsilon$ by using the Newton-Raphson Method to derive $\tilde{\lambda}$.
3. Construct new variables $\tilde{y} = (I_{NT} - \tilde{\lambda}W)\Delta y$ and $\tilde{z} = (I_{NT} - \tilde{\lambda}W)\Delta z$
4. Apply OLS for $\tilde{y}$ on $\tilde{z}$ to yield $\hat{\gamma}$.
5. Construct the new residuals $\hat{\tilde{u}} = \tilde{y} - \tilde{z}\hat{\gamma}$ and return to Step 2 to calculate $\hat{\lambda}$.
6. Construct the robust covariance for $\hat{\gamma}$ by calculating $\hat{A} = \frac{N}{N-K}(\tilde{z}'\hat{\tilde{u}}\hat{\tilde{u}}'\tilde{z})$.

Table A.3.1. Estimation Results for the Economic Growth-CO_2 Emissions Relationship (Quadratic Specification) with First-Order Contiguity Spatial Weight Matrix

	Model Types						
Explanatory Variables	**LSDV**	**Elhorst FE**	**Dynamic Elhorst FE**	**SFE**	**SFD**	**Dynamic SFE**	**Dynamic SFD**
$CO_{2,t-1}$	N/A	N/A	0.9707*** (185.499)	N/A	N/A	0.1570*** (3.8015)	0.0037 (0.7914)
GDP	12.6768*** (18.4822)	15.0137*** (10.625)	1.5783*** (4.7968)	11.4685*** (4.6129)	5.7066** (2.2805)	9.7192*** (4.9268)	5.3752** (1.9967)
GDP^2	-0.6196*** (-18.4207)	-0.7515*** (-10.7847)	-0.0788*** (-4.8548)	-0.5563*** (-4.5935)	-0.2705** (-2.1680)	-0.4791*** (-4.9997)	-0.2545** (-1.8993)
CDD	-0.0179 (-0.8664)	0.3211*** (22.5344)	0.0209*** (5.7876)	-0.0221 (-0.2481)	0.0131 (1.0463)	0.0072 (0.1526)	0.0137 (1.0342)
HDD	0.0692 (1.3415)	0.3511*** (16.4961)	0.0275*** (5.3541)	0.0470 (0.2799)	0.1020*** (3.4206)	0.1235 (1.3137)	0.1041*** (3.3132)
Coal	0.0015*** (10.1853)	0.0037*** (26.3362)	0.0001*** (2.6978)	0.0018* (2.0265)	0.0011 (1.3014)	0.0011** (2.0716)	0.0011 (1.2283)
Oil	-0.0008*** (-3.1082)	0.0037*** (25.387)	0.0003*** (8.9188)	0.001 (0.0974)	0.0005 (0.5272)	-0.0008 (-1.1204)	0.0005 (0.5174)
λ	N/A	-0.974*** (-6.5105)	-0.969*** (-6.4782)	-6.6092 (0.1134)	0.0085 (0.2364)	0.4985 (0.1183)	0.0094 (0.2396)
R^2	0.9402	0.6027	0.9796	0.6028	0.6019	0.7347	0.7347
Adjusted R^2	0.9371	0.5893	0.9789	0.5932	0.5934	0.7291	0.7289
Robust SE	No	No	No	Yes	Yes	Yes	Yes

Notes: The numbers in the parentheses denote t-statistics. The superscripts ―***", ―**", ―*" denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate. Parentheses for spatial autocorrelation coefficient (λ) represent chi-squared statistics determined by Burridge's LM test.

Table A.3.2. Estimation Results for the Economic Growth-CO_2 Emissions Relationship (Cubic Specification)

	Model Types				
Explanatory Variables	**LSDV**	**Elhorst FE**	**Elhorst UMLE**[34]	**SFE**	**SFD**
$CO_{2,t-1}$	N/A	N/A	0.9484*** (277.2292)	N/A	N/A
GDP	11.2151 (0.5618)	140.1052*** (3.3179)	0.6893*** (3.8034)	14.1584 (0.2199)	1.2503 (0.0212)
GDP^2	-0.4748 (-0.2403)	-13.136*** (-3.1434)	-0.0346*** (-3.9112)	-0.8229 (-0.1294)	0.1720 (0.0295)
GDP^3	-0.0048 (-0.0733)	0.4083*** (2.9641)	0.0001* (1.7157)	0.0088 (0.0420)	-0.0146 (-0.0760)
CDD	-0.0180 (-0.8677)	0.3228*** (22.6872)	0.0002 (0.1093)	-0.0221 (-0.2142)	0.0131 (0.9931)
HDD	0.0691 (1.3401)	0.3518*** (16.5658)	0.0022 (0.5961)	0.0470 (0.2426)	0.1020*** (3.2457)
Coal	0.0015*** (10.1484)	0.0037*** (26.2457)	0.0001*** (3.9357)	0.0018* (1.7474)	0.0011 (1.2341)
Oil	-0.0008*** (-3.0934)	0.0037*** (25.5919)	0.0001 (1.2768)	0.0001 (0.0828)	0.0005 (0.5031)
λ	N/A	-0.98*** (-6.5492)	-0.9978*** (-5.2203)	1.8823 (0.1135)	1.0259 (0.2358)
R^2	0.9402	0.6043	N/A	0.6044	0.6038
Adjusted R^2	0.9371	N/A	N/A	0.5947	0.5951
Robust SE	No	No	No	Yes	Yes
Notes: The numbers in the parentheses denote t-statistics. The superscripts —***”, —**”, —*” denote a significance level 0.01, 0.05, and 0.10 respectively. LSDV denotes the least squares dummy variable estimate.					

[34] These estimates are based upon the Bhargave-Sargan Approach outlined in Elhorst (2005).

CHAPTER 4. THE ROLE OF TECHNOLOGY IN ECONOMIC GROWTH AND ENVIRONMENTAL DEGRADATION

Chapter 3 offered a traditional approach to empirically modeling the EKC hypothesis. The existing modeling approach is still valuable and offers important policy prescriptions, for example, CO_2 emission reductions may require regional planning. However, the current empirical approach consists of only a reduced-form relationship between per-capita income and pollution; i.e., there is no theoretical explanation for the relationship between economic growth and pollution. Some skeptics view the EKC findings as a stylized fact. What is lacking in the literature is an explanation of the source of growth in the economy and how this source affects pollution levels. We seek to show that the diffusion of technology coupled with existing environmental policies drives the growth process while at the same time reducing pollution levels.

4.1 Introduction and Objectives

The advanced economies of the world have experienced immense growth in material wealth since the dawn of the Industrial Revolution. In the U.S. alone real per capita gross domestic product (GDP)[35] grew by a factor of 8.1 from 1870 to 1990—which corresponds to a growth rate of 1.75 percent per year (Barro & Sala-i-Martin,

[35] Through the rest of this chapter we will use the words GDP, national income (or just income), and output interchangeably.

Economic Growth, 1999).[36] For these industrialized economies (and several developing economies) this gain in material wealth has offered a better quality of life and several other social benefits, but these gains have not come without some costs as well.

By the late 20th century economic growth began to be seen as one of the main determining factors of environmental degradation and natural resource depletion. These criticisms became even more pronounced in the early 1970s with the publication of *Limits to Growth* in which the authors claimed that the world's rapidly depleting natural resource base could not continually support unfettered economic growth. Since that time many economists have argued that economic growth could be compatible with improvements in certain pollution problems.

Over the past few decades economists, seeking to explain the relationship between the natural world and economic growth, have incorporated an environmental component (such as non-renewable resources, pollution, etc.) into both neoclassical models and new growth models. The environment-growth models have become even more popular with the growth of the environmental Kuznets curve (EKC) literature which came to prominence in the early 1990s.[37] To date the practical lessons from this theoretical literature are limited. Most of the models, often with overly restrictive assumptions, are designed to yield inverted U-shaped pollution-income paths consistent with the EKC hypothesis (Levinson, 2008).

We are interested in analyzing the economic growth-pollution relationship largely consistent with the EKC literature. However, we argue that in addition to per-

[36] All estimates are measured in 1985 dollars.
[37] Throughout the rest of the chapter we use the phrase ―inverted-U shaped relationship" interchangeably with EKC.

capita income growth, a reduction in pollution levels result from R&D investments in clean technologies which are driven by the growing social awareness of environmental problems such as global climate change. Our model for the economic growth-pollution relationship is similar to the EKC literature in a general sense in that agents in developing countries possibly need a high marginal disutility of income (relative to the marginal utility of income) to institute costly abatement mechanisms. However we argue that per-capita income growth is not sufficient in itself to invoke reductions in pollution levels.

To better understand our economic growth-pollution relationship argument, we will analyze the behavior of a theoretical closed economy. By examining a closed economy we can better understand the mechanisms that drive reductions in pollution (or improvements in environmental quality). The objective is to derive the steady-state growth paths of the developed economy and explore the mechanisms that lead to a reduction in pollution levels. Following this framework we will offer a new theory of economic growth (incorporating an environmental component) in which technological change occurs as a result of private incentives for pollution-abating innovations. This new framework differs from several past EKC endogenous growth models that use the linear ―AK" technology assumption. In this new framework, pollution is modeled as a by-product of production that has a negative effect on environmental quality. A benevolent government is assumed to engage in environmental clean-up policies. Within this framework, this study seeks to determine if pollution emissions can decrease while an economy expands over time. Policy implications for the economy will then be explored on the basis of tradeoffs between private incentives for abatement and government-imposed disincentives in the form of abatement policies. Consistent with the EKC, we predict that pollution emissions follow the conventional inverted-U shaped relationship as new clean-tech innovations enter the market over time.

This chapter is organized as follows. The first section will offer a brief review of the theoretical EKC literature. The second section will set up the theoretical model and describe the innovation process. The third section will offer the analytical results from the model. The fourth section will offer a numerical analysis of the model to lend validity to it. The fifth section will discuss conclusions and limitations.

4.1.1 Literature Review

The history of the role of environmental and natural resources in economic growth dates back the 19th century writings of Malthus, Mill, and Jevons. These writings defined land as the natural resource of concern and recognized how its scarcity could affect economic growth. In modern times economists have developed a renewed interest in the relationship between the natural world (i.e., the environment and natural resources) and economic growth starting with the growing environmentalist movement of the 1960s and 1970s and the oil market shocks of the early 1970's. According to Toman (2003) the modern literature of this relationship can largely be divided into four categories: 1) growth and natural resource depletion; 2) growth and natural resource or environmental degradation; 3) trade, development, and the environment; and 4) endogenous growth and the environment.

The first generation of writings on the relationship between the natural world and economic growth concerned the depletion of world's natural resources. The notion of natural resource depletion captured the popular imagination after the publication of a famous monograph entitled *The Limits to Growth*. This ―limits-to-growth” debate induced several economists to redefine the notion of capital in the neoclassical growth models (Dasgupta and Heal, 1974; Solow, 1974; Stiglitz, 1974; Hartwick, 1977). Aggregate capital was often redefined to allow depletable natural resources to enter the production function as a separate form of capital.

Starting in the 1970s and continuing through today several economists started to recognize pollution as a negative by-product of economic activity. These scientists acknowledged that pollution could accumulate in the natural environment and cause considerable social costs. The social costs may come in the form of negative health effects from reduced air quality or limitations to production potential when the reduction of environmental quality necessitates intensive clean up or abatement efforts. Nordhaus (1992), for example, examines the economic efficiency of several policy prescriptions aimed at slowing global climate change.

Developing rapidly in the 1990s and through today the research on trade, development, and the environment now seems to make up a significant portion of the literature on the relationship between the natural world and economic growth. One particular work by Grossman and Krueger (1991) investigated the environmental consequences of the North American Free Trade Agreement on Mexico. The authors claimed that economic expansion through trade liberalization could lead to structural changes in Mexico’s economy that would favor more environmentally friendly modes of production. The authors found that sulfur emissions and smoke followed an inverted-U shaped relationship through time during a country’s course of economic expansion. Their work implied that NAFTA could potentially improve Mexico's pollution emissions. Several subsequent studies seemed to confirm Grossman and Krueger's (1991; 1995) findings (Shafik and Bandyopadhyay, 1992; Seldon and Song, 1994; Andreoni and Levinson, 1998).

As the EKC proposed hypothesis is only composed of a reduced form relationship between income and pollution levels, economist quickly became interested in developing a theoretical (or structural) model to explain the EKC relationship. Endogenous growth models (EGMs) have been one of the more popular approaches to explain this relationship (Elbasha and Roe, 1996; Aghion and Howitt, 1998; Stockey, 1998; Panayotou, 2000; Kwon, 2001; Lieb, 2002; Lieb, 2005; Hartman and Kwon, 2005; Dinda, 2005; Chimeli and Braden, 2005; Perez and Ruiz, 2007; Rubio et al., 2009). These EGMs often include the general notion that the marginal product of human-supplied capital (which incorporates not only equipment but human knowledge and skills) broadly defined does not decline towards zero as the volume of national capital grows (Toman, 2003).[38]

Chimeli and Braden (2005) develop an EGM in which economic growth is driven by total factor productivity (TFP), which has implications for environmental quality. TFP is the portion of output not explained by the amount of inputs used in production (Comin, 2006).[39] Chimeli and Braden specify a non-linear ―AK" production function where *A* denotes the TFP parameter and *K* is human-supplied

[38] In other words, the authors assume no diminishing marginal productivity of capital. Intuitively, this can be thought of as a ―learning-while-doing" process.
[39] Aggregate capital and labor usually do not explain all of aggregate output, so it is often argued that technological growth must make up the difference; this is sometimes referred to as the Solow residual.

capital.[40] As Comin (2006) points out, TFP plays a critical role on economic fluctuations, economic growth, and cross-country per capita income differences, so Chimeli and Braden were correct in using TFP to explain the path of pollution emissions over time (and varying across countries). However, Comin (2006) contends that the conceptual difficulty with endogenizing TFP growth is how to pay for the fixed costs of innovation in a perfectly competitive economy with constant returns to scale in capital and labor.[41] Romer (1980) solved this problem by granting the innovator monopolistic rights over her innovation, which are sustainable through the patent system. By linking the TFP growth rate to innovation, EGMs shed light on the determinants of TFP growth (Comin, 2006).

Thus, our model seeks to expand upon the work of Chimeli and Braden (2005) by incorporating technological innovation as the source for TFP growth. The structure of the overall model is fairly similar to Chimeli and Braden (2005), but the innovation process will be modeled after Barro and Sala-i-Martin (2004). The model has the basic structure of Barro and Sala-i-Martin (2004), but we adapt the model by adding pollution taxes, environmental protection efforts, pollution emissions, and the planet's natural ability to regenerate itself from pollution. We will expand Chimeli and Braden's (2005) model a little further by allowing innovations (which we describe as "clean" technologies) to reduce pollution in addition to public abatement efforts.

[40] We will explain the significance of the parameter *A* later in this chapter.
[41] In fairness to Chimeli and Braden (2005), the authors do not assume constant returns to scale in production, but the intuition of Comin's criticism is that an explanation for TFP growth makes for a more realistic model. In other words, Chimeli and Braden use TFP growth abstractly in their model.

The model consists of four different agents. The first agent, households, maximizes utility (a function of consumption and pollution as a public bad) subject to the household's budget constraint. This model differs from most past studies that have treated pollution as a choice variable in the utility function.[42] We argue that pollution has qualities similar to that of a public good (i.e., non-excludability and non-rival)—as such households receive disutility from pollution so as a public "bad." The second agent consists of a perfectly competitive sector of final output that hires labor (from households) and uses intermediate inputs in their production process. The third agent, R&D firms, devotes resources to invent clean technology innovations from which these firms receive patent rights. The patent for these innovations give the R&D firm a certain level of monopoly power to set prices which the firm chooses to maximize profits. The fourth and final agent is a benevolent national government that engages in clean-up policies that improves environmental quality within the economy.

Pollution enters the model as a by-product of production (from the final output sector) and is abated by clean-up efforts. Pollution which is assumed to be a pure public "bad" has a negative effect on environmental quality which is assumed to be a pure public good. As a public bad, producers do not internalize the social costs associated with their pollution activities resulting in market failure. To account for market failure, the government acts as regulator to capture the social costs associated with pollution by-products. The pollution levels are abated through government policies that are financed by some pollution-abating mechanism such as a Pigovian

[42] It is possible in some abstract sense that an agent can choose a certain level of pollution (e.g., driving a more fuel efficient vehicle), but this study treats environmental quality as a pure public good and pollution as a pure public "bad" (i.e., non-excludable and non-rival in consumption).

tax or a cap-and-trade mechanism.[43] Further, the clean technology innovations (invented by the R&D sector) reduce pollution emissions for the producers of final output. Therefore, in some cases the final producer has incentives to use the cleaner technology to hedge against costly pollution abatement policies. Within this framework, the long-run growth rate of the economy is a function of the interplay between governmental policies and private (clean) technological innovations.

The purpose of the current study is to analyze the balanced economic growth path (or steady state) of the economy based upon the interaction between technological innovation and governmental clean-up policies. Based upon a theoretical social planner's solution (the Pareto optimal solution), we will examine different levels of innovation and clean-up policies to determine how this affects the economy's long-run growth path of output, pollution, and pollution intensity.

4.1.2 Historical US Pollution Emissions

Under the US Clean Air Act, the US EPA monitors six common types of air pollution emissions which it calls the *criteria pollutants*. These pollutants are carbon monoxide, ozone, lead, nitrogen dioxide, particulate matter, and sulfur dioxide. In 2000 the EPA published the ―The National Air Pollutant Emission Trends Report, 1900-1998," (US EPA, 2000) in which the EPA described the trends of the criteria pollutants in the US over the last century. Figure 4.1 contains projections of the trends for each of the individual criteria pollutants. We obtained this figure from Brock and Taylor (2004). Each of the pollutants show a rise and then fall of emissions over the last century. According to Brock and Taylor (2004), the US

[43] A Pigovian tax is a tax levied on a market activity that generates negative externalities. When negative externalities occur the social costs of market activities are not covered in the private cost of the activity, so that the market outcome is not efficient.

experienced growth in real per-capita income of about two percent per year over this same period. Hence the EKC pattern seems apparent with these pollutants except for nitrogen dioxide (NO_x) which appears to be monotonically increasing over this period. A more recent review of the NO_x emissions data from 1980-2009 however shows a downward trend in these national emissions over this revised period (US EPA, 2010).

Figure 4.1. Historic US Pollution Emissions

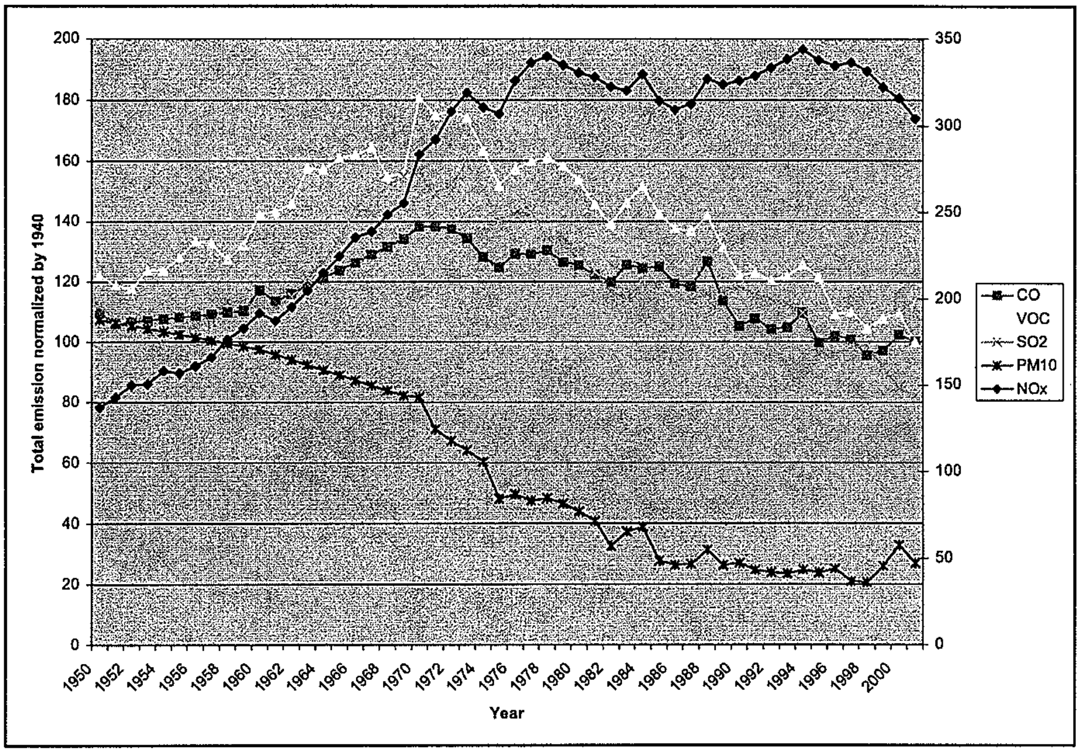
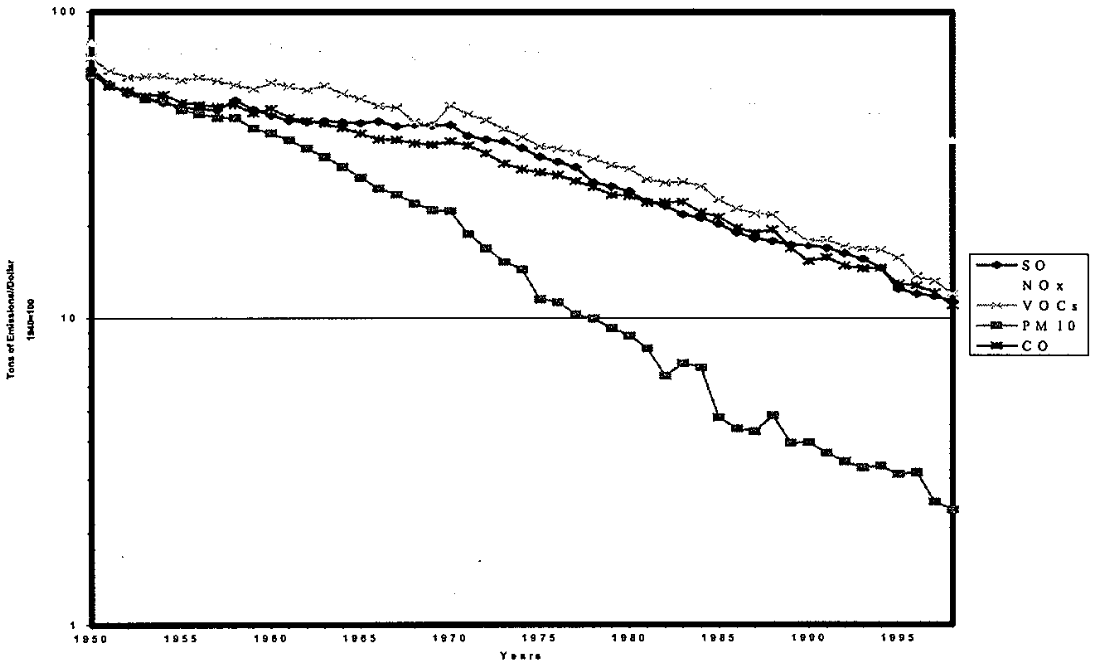


Figure 4.2 shows pollution intensities over the second half of last century. This figure again too was taken from Brock and Taylor (2004). Pollution intensity is a measure of emission per dollar of real GDP. Brock and Taylor (2004) adopted a log scale for ease of reading. According to the authors, there are two things worth noting about Figure 4.2. One, pollution to output has been declining in the US since 1950.

Two, the percentage rate of decline has been roughly constant over the fifty-year period.

Figure 4.2. Historic US Pollution Intensities



With our theoretical model we seek to show the driver of these trends (i.e., pollution emissions and intensities). In the following section we will develop the private sector's (i.e., a decentralized economy) optimal levels of consumption, intermediate goods, output, etc. Next, we will turn our attention to the social planner's solution (i.e., a centralized economy) to develop the Pareto optimal conditions for the economy. We will discover that the growth of consumption, output, and intermediate goods will grow slower in the centralized economy because the benevolent social planner internalizes the net cost of pollution emissions into production. Further, we will see how increasing returns to scale in innovations lead to the inverted-U shape relationship consistent with the trends in Figures 4.1 and 4.2.

4.1.3 State of Clean Technology Innovation and Total U.S. R&D Expenditures

The Cleantech Group (2010) publishes a quarterly clean energy patent growth index. According to their most recent report the number of U.S. patents for clean-energy technologies in 2009 was at an all time high at 1125.[44] Patents for fuel cells and hybrid/electric vehicles were up 20% over 2008. Solar patents were up 60% and biomass/biofuels patents were up 260%. Fuel cells, wind, and biomass/biofuels patents were also at an all time high in 2009. Fuel cell patents dwarf the other sectors with over four times the number of patents of its closest competitors wind and solar.

Further, the Cleantech Group (2010) claims that North America raised $3.5 billion in venture capital investment for clean technologies in 2009; this number is down 42% from 2008 and down 17% from 2007. The leading sector was solar with 22% of total investment, closely followed by transportation and energy efficiency. Pernick and Wilder (2007) argue that U.S.-based venture capital in clean energy technologies increased from $599 million in 2000 to $2.7 billion in 2007. Through the American Recovery and Reinvestment Act the U.S. federal government plans to dedicate $97 billion towards research, development, and deployment of clean energy technologies (Jacobs and McNish, 2009).

Figure 4.3, derived from Payson (1999), shows the general trend of total aggregate R&D expenditures as a percentage of GDP over the last half century in the US. In the short run there are considerable fluctuations in the percentages, but average R&D expenditures as a percentage of GDP was approximately 2.58% during this period. During this same period the average growth of GDP was approximately 3.3%; therefore, the growth of R&D expenditures (as a proxy for new technologies) and GDP were fairly similar during this period (US Department of Commerce, 2009).

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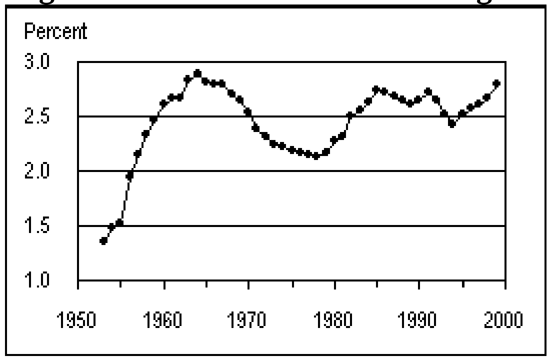
[44] Due to data limitations it is difficult to measure the actual number of new clean technology innovations. It is much easier to measure R&D expenditures in general so we will use it as a proxy for clean technology innovations.

Figure 4.3. US R&D as a Percentage of GDP



NOTES: These data are based on reports from R&D performers. Data for 1998 and 1999 are preliminary.

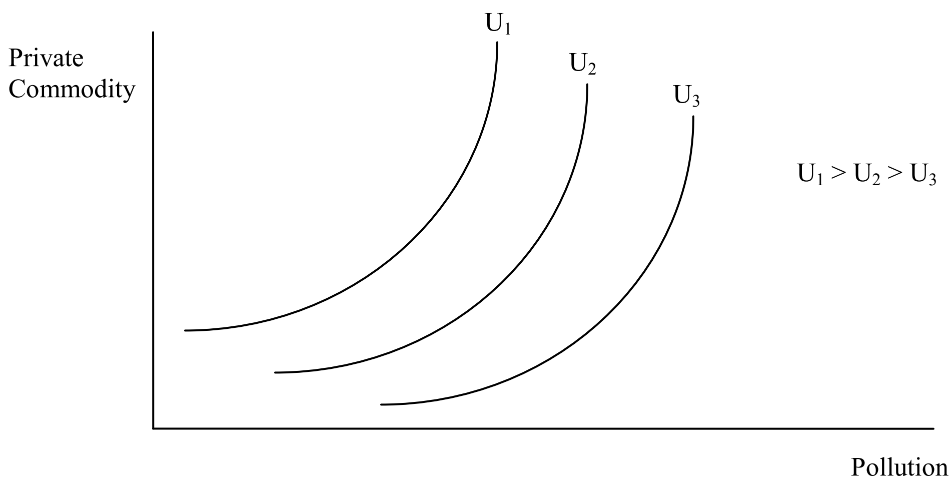
SOURCE: National Science Foundation/Division of Science Resources Studies. These data were derived from data collected in three SRS surveys: Survey of Industrial Research and Development, Survey of Research and Development Expenditures at Universities and Colleges, and Survey of Federal Funds for Research and Development.

4.2 Private Sector Solution and Model Setup

4.2.1 Households

Pollution, *P*, is affected by production activities. We assume that pollution is a pure public "bad." According to Sonnemans et al. (1998), the problem of preventing a public bad is equivalent to the problem of providing a public good. The assumption of pollution being a public bad is a subtle but important distinction. Past studies often assume that pollution enters as a choice variable into the utility function as assumed, for example, by Andreoni and Levinson (1998). However, when we are modeling an entire economy with many different agents, it becomes increasingly more difficult to assume that each agent has control over economy-wide pollution levels. A richer assumption implies that pollution, as an externality, is composed of qualities similar to a public good; i.e., pollution as a pure public bad is non-excludable and non-rival (Baumol and Oates, 1975; Kolstad 2010). It is assumed that households derive positive marginal utility from private goods consumed and negative marginal utility from pollution. This assumption of utility implies that for a household to be willing to consume more of the bad good (pollution), it must be compensated with more of the private commodity as illustrated in Figure 4.4 below (Wetzstein 2005). Thus, our assumption of pollution as a pure public bad is subtle but it will have an effect on the socially optimal amount of expenditures on pollution abatement.[45]

Figure 4.4. Indifference Curves with Pollution as a Pure Public Bad



For simplicity we assume that the economy consists of a homogenous set of households that maximize utility over an infinite horizon with perfect foresight. We abstract away from issues concerning population growth and labor supply. Specifically, we assume each household offers a unit of labor inelastically to either the final output firms or the R&D firms. It is assumed that households own capital

[45] This assumption is similar to that of Chimeli and Braden (2005) who model environmental quality as a public good. As Sonnemans et al. (1998) contend, our approach is strategically equivalent to Chimeli and Braden (2005), only we are seeking to prevent a public bad (pollution) whereas Chimeli and Braden (2005) seek to provide a public good (environmental quality).

(or *assets*) which they rent to firms and from which they receive a return. So wealth in this economy is held by the representative household in form of assets.[46]

We assume that each household contains one or more adults who are part of the current working generation. These adults take into account the welfare of their descendents, so that although the adults have finite lives they consider intergenerational transfers to their offspring. This intergeneration transfer is incorporated into the model whereby current adults maximize utility over an infinite horizon. Thus, working members, *L*, in the model correspond to the current adult population. For ease of analysis we will assume that the current population growth rate is exogenous and growing at the fixed rate, *n*. Thus, the population can be specified as $L = e^{nt}$. Assuming a fixed population growth rate helps us to abstract from the effects of population growth on consumption and environmental protection efforts. Based on these assumptions, an agent maximizes his or her present value of utility according to

$$\text{Maximize } W = \int_0^{\infty} e^{-(\rho - n)t} u\left[c(t), P(t)\right] \qquad (4.1)$$

$$U_c > 0;\ U_P < 0;\ U_{cc} < 0;\ U_{PP} > 0;\ U_{cP} < 0$$

where *c* denotes consumption, ρ is the discount rate, *n* is the constant population growth rate, and *P* is the pure public bad of environmental pollution. The optimal present value of all future welfare for the representative household is obtained my maximizing equation (4.1) subject to the household's budget constraint,

[46] Wealth held in the form of assets simplifies the model so that complications with money transaction costs or monetary policy do not have to be considered.

$$\frac{d(assets)}{dt} = w(t)\cdot L(t) + r(t)\cdot(assets(t)) - C(t). \qquad (4.2)$$

Households earn the rate of return r on assets and receive the wage rate w on the fixed aggregate quantity L of labor and C denotes aggregate consumption. We will discuss the budget constraint more thoroughly below (including the specific definition of *assets*), but basically equation (4.2) implies that in each point in time income (wL + $r\cdot$(*assets*)) must be allocated towards consumption and implicitly with environmental protection efforts (we will see this later in the study).

4.2.2 Producers of Final Output

The producers of final output have a production technology that combines labor with a number of intermediate inputs to produce final goods. The final goods are sold in a perfectly competitive market. The production function of firm i takes the following form[47]

$$Y^i(t) = A\left[L^i(t)\right]^{1-\alpha}\sum_{j=1}^{N}\left[X^{ij}(t)\right]^{\alpha} \qquad (4.3)$$

$$Y_L^i, Y_{X_j}^i > 0;\ Y_{LL}^i, Y_{XX}^i < 0;\ Y^i(\gamma L^i, \gamma X^{ij}) = \gamma Y^i(L^i, X^{ij});$$

where α denotes the output elasticity of intermediate goods $(0 < \alpha < 1)$, Y^i is output, A is the productivity parameter, L^i is the labor input, and X^{ij} is the use of the jth type of intermediate input into the production process.[48] Y, L, and X are all functions of time,

[47] We assume the standard Inada conditions for (4.3) which are $\lim_{X\to 0}\left(\frac{\partial Y}{\partial X}\right) = \lim_{L\to 0}\left(\frac{\partial Y}{\partial L}\right) = \infty$ and $\lim_{X\to\infty}\left(\frac{\partial Y}{\partial X}\right) = \lim_{L\to\infty}\left(\frac{\partial Y}{\partial L}\right) = 0,$ which implies that output is concave in labor and intermediates.

[48] Equation (4.3) implies Hicks neutral technological progress; i.e., the productivity parameter, A, does not affect the balance of labor or capital.

but for ease of exposition the time functions have been removed from some of the subsequent derivations. The production function in (4.3) implies diminishing marginal productivity of each input and constant returns to scale in all inputs together. Profit for the producer of final goods is

$$\Pi^i(t) = [1-\tau(t)]Y^i(t) - w(t)\cdot L^i(t) - \sum_j^N P^j(t)\cdot X^{ij}(t), \tag{4.4}$$

where w denotes the wage rate, P^j is the price of intermediate good j, L^i is the total labor used by firm i, and τ is the unit tax levied against the pollution activities of the firm.[49] To simplify the analysis we will assume that output prices equal unity to abstract from output price growth rates in the rest of the analysis. Since the firms are competitive they take w and P^j as given. We will see later in the chapter that the environmental protection efforts (offered by a governmental entity) will run a budget that is a function of the tax collections which is denoted by τY. We will consider how environmental protection efforts enter into the economy later in the analysis.

The production function in equation (4.3) implies that the marginal product of the jth intermediate input is

$$\frac{\partial Y^i}{\partial X^{ij}} = \alpha A\left(L^i\right)^{1-\alpha}\left(X^{ij}\right)^{\alpha-1}. \tag{4.5}$$

Next, we take the derivative of the jth intermediate input with respect to the profit function in equation (4.4) to derive the input demand function for the intermediate good

[49] Please note that P^j denotes a price whereas P without the j subscript denotes to pollution.

$$\frac{\partial \Pi^i}{\partial X^{ij}} = [1-\tau]\frac{\partial Y^i}{\partial X^{ij}} - P^j = 0$$

$$= (1-\tau)\left[\alpha A\left(L^i\right)^{1-\alpha}\left(X^{ij}\right)^{\alpha-1}\right] - P^j = 0 \qquad (4.6)$$

$$\Rightarrow X^{ij} = L^i\left[\frac{\alpha A(1-\tau)}{P^j}\right]^{1/(1-\alpha)}.$$

Summing across all *i* firms of final output yields the aggregate demand function for good *j*:

$$X^j = L\left[\frac{\alpha(1-\tau)A}{P^j}\right]^{1/(1-\alpha)}. \qquad (4.7)$$

Equation (4.7) implies that the demand for good *j* is increasing in the productivity parameter, *A*, aggregate labor, and decreasing in the input price, P^j, and the pollution tax, τ.

To derive the input demand for labor we take the derivative of the profit function with respect to labor which yields

$$w = (1-\alpha)\frac{Y^i}{L^i}. \qquad (4.8)$$

4.2.3 Intermediate Goods (R&D) Firms

A current level of technology exists to produce the *N* intermediate goods. Technological progress within the economy follows from expansions in the number of specialized intermediate goods, *N*, available as inputs in the economy.[50] This differs from other endogenous growth models in the EKC literature where authors

[50] In this sense technological advancement constitutes a horizontal innovation process as opposed to a vertical innovation process. With a horizontal innovation process new inventions supplement or complement current intermediate goods; in other words, new innovations do not necessarily render incumbent intermediaries (intermediate goods) as obsolete. A vertical innovation process constitutes better quality inventions that render incumbent intermediaries as obsolete.

often (implicitly) assume that expansion of A, the productivity parameter, leads to the technological progress. An interpretation of A is that firms' production processes improve over time because the firms learn on the job; e.g., a coal-fired electricity plant will learn to generate electricity more efficiently over time. By incorporating N into the analysis we are assuming that improvements in electricity production take place not only because of learning-while-doing but also because R&D firms invent specialized technologies, such as IGCC, to generate electricity more efficiently. In the present analysis we interpret these innovations as being more environmental friendly forms of technology (so called ―clean-tech" or clean technologies) that make production processes more efficient but also reduce pollution levels.[51] For example, Integrated gasification combined cycle (IGCC) is a technology that turns coal into a gas and then removes the impurities from the gas prior to combustion. IGCC offers improved production efficiencies compared to conventional pulverized coal (US DOE, 2010). Thus, the new technology causes improvements in production and there are less environmental damages.

New innovations are developed by the R&D sector. R&D firms have a two-stage decision process. In the first stage they must decide whether to devote resources to the invention of a new intermediate good. If the net present value of future expected profits is larger than the R&D expenses paid up front then the firm will use its resources to invent the new good. In the second stage the firms determine the optimal price to sell their newly invented good to the producers of final output. The R&D firms are assumed to obtain patent rights which give the firms virtual

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[51] Throughout the rest of this chapter we refer to these clean technologies as clean-tech or simply new innovations interchangeably.

monopoly power in the production and sale of their newly invented good. The forecasted price in turn determines the flow of profits in each period from which the inventor can determine the present value of profits in the first stage of the decision process.

In other words, the R&D firms work backwards by first determining the present value of expected profits flows in the second stage and then determining to dedicate resources towards R&D development in the first stage. We explore this process more thoroughly in the next two subsections.

4.2.3.1 Second Stage

The R&D firms must first estimate the present value of all future profits from the new invention. The estimate of the net present value (NPV) of future returns is given by

$$V(t) = \int_{t}^{\infty} \pi_j(\upsilon) \cdot e^{-\bar{r}(t,\upsilon)\cdot(\upsilon - t)} d(\upsilon), \tag{4.9}$$

where π denotes the profit flow at date υ and $\bar{r}$ is the average interest rate between times t and υ. The R&D firm's revenue at each date equals the price, $P^j(\upsilon)$, times the amount of the new good j sold. The flow of profits equals the revenues minus production costs. We assume, without loss of generality, that marginal and average costs of production are constant, and normalized to one. The flow of profits then is given by

$$\pi(\upsilon) = (P^j(\upsilon) - 1) \cdot X^j(\upsilon) \tag{4.10}$$

where

$$X^j(\upsilon) = \sum_i X^{ij}(\upsilon) = X^j\left(AL, \tau, P^j(\upsilon)\right) \tag{4.11}$$

X^{ij} denotes the intermediate goods used for production by industry *i*. By summing the intermediate goods over *i* in (4.11) we are deriving the total amount demanded within each particular industry—the aggregate input demand function corresponds with equation (4.6) above. Based upon this demand the producer of X^j can select P^j at each date to maximize the flow of monopoly profit at that date. The profit maximization function for the new inventor is then

$$\max_{P^j} \pi(\upsilon) = \left(P^j(\upsilon) - 1\right) \cdot X^j\left(AL, \tau, P^j(\upsilon)\right)$$
$$= \left(P^j(\upsilon) - 1\right) L \left[\frac{\alpha(1-\tau)A}{P^j(\upsilon)}\right]^{1/(1-\alpha)}, \tag{4.12}$$

where $P^j(\upsilon)$ is the price at date υ. Maximizing equation (4.12) with respect to the price P^j yields the solution for the monopoly price offered by the inventor which is

$$P^j = \frac{1}{\alpha} > 1. \tag{4.13}$$

The optimal price or markup is the reciprocal of the output elasticity of intermediate goods, α. If we substitute the optimal price P^j into the input factor demand function (equation (4.7)) then we can determine the aggregate quantity produced of each intermediate good:

$$X^j = L[A(1-\tau)]^{1/(1-\alpha)} \alpha^{2/(1-\alpha)}. \tag{4.14}$$

If we rewrite equation (4.14) to account for total demand of X^j in the economy then we get

$$X = NX^j = [A(1-\tau)]^{1/(1-\alpha)} \alpha^{2/(1-\alpha)} LN. \tag{4.15}$$

If we substitute equation (4.15) into the aggregate output function (4.3) then we get

$$Y = AL^{1-\alpha} X^\alpha N^{1-\alpha} = A^{1/(1-\alpha)} [(1-\tau)]^{\alpha/(1-\alpha)} \alpha^{2\alpha/(1-\alpha)} LN. \tag{4.16}$$

We can now substitute the optimal price P^j into the profit maximization function for the inventor (equation (4.12)) to determine the optimal profit flow. Finally, we substitute (4.15) into the profit function (4.12) to derive the flow of profits:

$$\pi_j(\upsilon) = \pi = \left(\frac{1-\alpha}{\alpha}\right)[A(1-\tau)]^{1/(1-\alpha)}\alpha^{2/(1-\alpha)}L. \tag{4.17}$$

If we substitute equation (4.17) into the value function (4.9) then we derive the inventors present value of profits at time t

$$V(t) = \left(\frac{1-\alpha}{\alpha}\right)[A\cdot(1-\tau)]^{1/(1-\alpha)}\cdot\alpha^{2/(1-\alpha)}\cdot L\cdot N\cdot\int_t^{\infty} e^{-\bar{r}(t,\upsilon)\cdot(\upsilon-t)}d\upsilon, \tag{4.18}$$

where

$$\bar{r}(t,\upsilon) \equiv \left[\frac{1}{(\upsilon-t)}\right]\cdot\int_t^{\upsilon} r(\omega)d\omega \tag{4.19}$$

is the average interest rate between t and υ (Baro and Sala-i-Martin, 2004).

4.2.3.2 First Stage

The virtual monopoly rights allow the inventor to collect the present value in equation (4.19). The firm will decide to devote resources towards the new invention if the present value of future profits outweighs the R&D costs. Thus, R&D investment depends on R&D costs. A realistic explanation for the research process would include uncertainty about the amount of resources necessary to develop an innovation; however, in order to simplify our analysis we will assume that the development process requires a deterministic amount of resources. Specifically, we will assume that cost to develop a new type of innovation is η of Y. One could argue that it becomes more difficult to develop new inventions if there are already a large number of similar inventions current in the market, then the research costs would be an increasing function of the number of innovations on the market, $\eta'(N) > 0$. Conversely, one could argue that developing new inventions becomes easier over time because preceding inventions make it easier to develop newer or more complicated inventions; i.e., the innovation process builds on itself. If this were the case then the research costs would be a decreasing function of the number of innovations in the market, $\eta'(N) < 0$. To simplify we will assume that these two effects will approximately cancel one another out over time so that R&D costs grows at the constant rate, η. Ergo, the R&D firm will decide to dedicate resources towards innovation if $V(t) \geq \eta$.

We assume that there is free entry into the R&D industry whereby anyone can choose to invest the R&D cost, η, to obtain the net present value of future profits, $V(t)$. If $V(t) > \eta$ then all the R&D firms would dedicate resources towards the innovation process which cannot hold in equilibrium. Conversely, if $V(t) < \eta$ then no R&D firms would dedicate resources and so innovations would not expand over time—this condition would not hold in equilibrium either. So, given free-entry the net present value of future profits flows equals the R&D costs

$$V(t) = \eta. \tag{4.20}$$

If we differentiate equation (4.20) with respect to time and solve for r then we derive[52]

$$r(t) = \frac{\pi}{V(t)} + \frac{\dot{V}(t)}{V(t)}. \tag{4.21}$$

[52] See Barro and Sala-i-Martin (2004) for the derivation of (4.21).

Since η is constant as in (4.20) then it implies that $\dot{V}(t) = 0$ in equation (4.21), so we can substitute equations (4.18) and (4.20) into (4.21) to derive

$$r(t) = r = \left(\frac{L}{\eta}\right) \cdot \left(\frac{1-\alpha}{\alpha}\right) \cdot \left[A \cdot (1-\tau)\right]^{1/(1-\alpha)} \cdot \alpha^{2/(1-\alpha)}. \tag{4.22}$$

The underlying rate of return and the market structure equate the rate of return, *r*, to the RHS in equation (4.22).

4.2.4 Central Government (Regulator)

The central government is assumed to levy a unit tax, τ, $(0 \leq \tau < 1)$ on the pollution created in the production process of final goods.[53] The government finances its clean-up policies through these tax revenues, τY. The tax revenues are used to abate pollution emissions. We will assume that the government will reallocate the tax revenues as a lump-sum payment towards pollution abatement.

4.2.5 Pollution

The equation of motion for environmental pollution is assumed to be generated by the following process,

$$\begin{aligned} \dot{P} &= \Omega \cdot Y - \tau \cdot Y - \Omega \cdot N^{\varepsilon} - \phi \cdot P \\ &= \Omega Y \cdot a(\theta) \end{aligned} \tag{4.23}$$

$$\text{where } a(\theta) \equiv \left[1 - \left(\frac{\tau}{\Omega}\right) - \theta - \frac{\phi}{\Omega}\frac{P}{Y}\right] \text{ and } \theta = \frac{\mathrm{N}^{\varepsilon}}{\mathrm{Y}},\ \varepsilon > 1.$$

where *Ω* is a unit of pollution which is generated as a joint product of output and τ denotes the per-unit tax on final output.[54] *Ω* can also be interpreted as the baseline

[53] It would be too costly for the government to calculate the amount of pollution from each producer, so it levees the tax against a unit of the final good produced.
[54] With this specification of pollution we follow Copeland and Taylor (1994), Aghion and Howitt (1998), Brock and Taylor (2004), and Criado, Valente, and Stengos (2009).

emission intensity (Criado et al., 2009). $\phi > 0$ denotes natures regenerative ability (Brock and Taylor, 2004).[55]

With this specification we assume that the governmental regulator reallocates the tax revenue as a lump-sum payment to abate pollution; one can think of this as public abatement efforts. We also assume however that clean-tech innovation reduces pollution, but the creation of such technologies also creates pollution; one can think of this as private abatement efforts. Our specification is almost identical to that of Brock and Taylor (2004) who instead assume $a(\theta) = (1-\theta)^{\varepsilon}$ because they do not differentiate between public and private abatement activities. In our analysis we assume that that private abatement efforts (clean-tech innovations) offer increasing returns to scale (IRS)—this assumption is captured with $\varepsilon > 1$ in (4.23). The IRS assumption is consistent with Andreoni and Levinson (1998) who found evidence of the EKC with this assumption. We will relax this assumption later in the analysis to see its effect on the economies long-run growth path of pollution emissions.

4.2.6 Equilibrium

Recall that households hold wealth in terms of assets which in the current framework is the value of firms in the market that are equal to $V(t)\cdot N$; i.e., the product of the NPV of innovations and the number of innovations in the market. Since we assumed free entry into the R&D industry, $V(t)$ is equal to the cost of R&D, η, so assets are equal to $\eta \cdot N$. Therefore, the change in assets over time is

$$\frac{d(assets)}{dt} = \eta \cdot \dot{N}. \tag{4.24}$$

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[55] Earth has a natural regenerative process where it partially filters pollution emissions from the planet's atmosphere.

Recall that the input demand for labor yielded (equation (4.8) above)

$$w = (1-\alpha)\frac{Y}{L}.$$

Additionally, we can manipulate the rate of return in equation (4.22) to yield[56]

$$r = \frac{1}{\eta}\cdot(1-\alpha)\cdot\alpha\cdot(1-\tau)\cdot\left(\frac{Y}{N}\right). \tag{4.25}$$

Aggregate income can be determined by adding labor income and return on assets (equation (4.2)) as *w·L + r·(assets).* Thus, after some manipulation aggregate income is equal to[57]

$$Y - X - \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X. \tag{4.26}$$

If we substitute aggregate income (equation (4.26) into the budget constraint (equation (4.2)) then the constraint becomes

$$\dot{N} = \left(\frac{1}{\eta}\right)\cdot\left[Y - X - \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X - C(t)\right], \tag{4.27}$$

where the aggregate intermediate goods, *X*, enter the budget because $X = \alpha^2\cdot(1-\tau)\cdot Y$. If we rearrange the budget constraint in (4.27) then we derive

$$Y = \eta\dot{N} + C + X + \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X. \tag{4.28}$$

The budget constraint therefore implies that in each point in time aggregate income, *Y*, is either allocated to the production of intermediate goods, *X*, the creation of new goods, $\dot{N}$, consumption, *C*, and/or to environmental protection efforts financed

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[56] The derivation of equation (4.25) is offered in the appendix.
[57] The derivation of equation (4.26) is offered in the appendix.

through, τ. The fourth term on the RHS of (4.28) is the *tax-exclusive rate* of the environmental tax.[58]

4.3 Social Planner Solution

We will now examine general equilibrium in the economy from the perspective of a hypothetical social planner. The role of the social planner is to maximize the utility of the representative household subject to the economy's budget constraint from equation (4.29). We can rewrite the budget constraint as follows

$$\dot{N} = \left(\frac{1}{\eta}\right)\left\{AL^{(1-\alpha)}X^{\alpha}N^{1-\alpha} - X - \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X - Lc\right\}, \qquad (4.29)$$

recall that L is the size of the adult population so we substitute $C = L{\cdot}c$, where c is per-capita consumption. With the specification in (4.29) we have implicitly imposed the condition that the quantity of intermediates is the same for all firms of final output i, and intermediate goods j (we saw this functional form in (4.16)). The social planner also maximizes utility according to the environmental quality constraint (one could think of this as environmental budget constraint) which is defined in equation (4.23) above.

The current-value Hamiltonian for the economy is based upon equations (4.1), (4.23), and (4.29):

[58] The Tax Policy Center (2010) refers to a tax-inclusive rate as the amount of tax paid of the after-tax value of a good. Conversely, a tax-exclusive rate is the amount paid as a proportion of the pretax value of a good. A sales tax is usually quoted at a tax-exclusive rate; e.g., if a good costs \$100 and the sales tax is \$30 then the good has a tax-exclusive rate of 30%. The tax-inclusive rate on the hand is lower because the sales tax amount is divided by the implicit cost for the good \$130, which is 23%. Mathematically, we are taking the tax-inclusive rate of final goods and converting it to the exclusive rate of intermediate goods. Notice that since the output elasticity of intermediates, α, is a fraction less than one, the coefficient on the term is greater than one which amplifies the tax-exclusive rate. Therefore, the greater the output elasticity the larger the affect on intermediate goods.

$$
\begin{aligned}
H &= u\left[c(t), P(t)\right] \\
&+v_1(t)\left(\frac{1}{\eta}\right)\left\{AL^{(1-\alpha)}X^{\alpha}N^{1-\alpha} - X - \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X - Lc\right\} \\
&+v_2(t)\left\{(\Omega-\tau)\cdot Y - \Omega\cdot N^{\varepsilon} - \phi\cdot P\right\},
\end{aligned}
\tag{4.30}
$$

where v_1 and v_2 are the shadow prices for $\dot{N}$ and $\dot{P}$ respectively. The control variables are c, τ, and X. The state variables are N and P. The tranversality conditions for (4.30) are $\lim_{t\to\infty}\left[N(t)\cdot v_1(t)\right]=0$ and $\lim_{t\to\infty}\left[P(t)\cdot v_2(t)\right]=0$. The conditions imply that if the number of innovations, $N(t)$, and pollution, $P(t)$, grow forever at a positive rate then the shadow prices ($v_1(t)$ and $v_2(t)$, respectively) must approach zero at a faster rate so that the products within the limits go to zero. A simple interpretation of the first limit (for innovations) is that optimizing agents would not want to have valuable assets left over at the end of the planning horizon. The second limit (for pollution) ensures that utility does not asymptotically approach zero.

The necessary conditions for an interior solution of the social planner's problem are:[59]

[59] The derivation of X in (4.31) is offered in the appendix.

$$
\begin{aligned}
v_1 &= \left(\frac{\eta}{L}\right)\cdot u_c \\
v_2 &= -\cdot\left(\frac{1}{\eta}\right)\cdot\left(\frac{\alpha}{1-\tau}\right)\cdot v_1 \\
X &= \left(\frac{\alpha^3}{1-\alpha}\right)^{1/(1-\alpha)}\left(\frac{\Omega-\tau}{1-\tau}\right)^{1/(1-\alpha)} A^{1/(1-\alpha)}LN \\
\dot{v}_1 &= -\frac{\partial H}{\partial N}+(\rho-n)\cdot v_1 = -v_1\cdot(1-\alpha)\cdot\left(\frac{1}{\eta}\right)\cdot\left(\frac{Y}{N}\right) \\
&-v_2\left\{(\Omega-\tau)\cdot(1-\alpha)\cdot\frac{Y}{N}+\Omega\varepsilon N^{\varepsilon-1}\right\}+(\rho-n)\cdot v_1 \\
\dot{v}_2 &= -\frac{\partial H}{\partial P}+(\rho-n)\cdot v_2 = -u_P+(\phi+\rho-n)\cdot v_2
\end{aligned}
\tag{4.31}
$$

Intermediates goods, X, in (4.31) above implies that final output is equal to

$$
Y = \left(\frac{\alpha^3}{1-\alpha}\right)^{\alpha/(1-\alpha)}\left(\frac{\Omega-\tau}{1-\tau}\right)^{\alpha/(1-\alpha)} A^{1/(1-\alpha)}LN. \tag{4.32}
$$

Manipulation of the necessary conditions leads to the following:[60]

$$
\dot{c} = \frac{u_c}{u_{cc}}\cdot\left\{\rho-\frac{u_{cP}}{u_c}\cdot\dot{P}+\psi\cdot\left(\frac{Y}{N}\right)-\left(\frac{1}{\eta}\right)\cdot\left(\frac{\alpha}{1-\tau}\right)\cdot\Omega\cdot\varepsilon\cdot N^{\varepsilon-1}\right\} \tag{4.33}
$$

$$
\dot{\tau} = (1-\tau)\cdot\left\{L\cdot\frac{u_P}{u_c}\cdot\left(\frac{1-\tau}{\alpha}\right)+\phi+\rho-\frac{u_{cc}}{u_c}\cdot\dot{c}-\frac{u_{cP}}{u_c}\cdot\dot{P}\right\}, \tag{4.34}
$$

where $\psi = \left(\frac{1}{\eta}\right)\cdot\left\{\left(\frac{\alpha}{1-\tau}\right)\cdot(\Omega-\tau)-1\right\}$. Equations (4.33) and (4.34) constitute the optimal growth rates of consumption and pollution tax policies. Recall from equation (4.1) that we assumed that utility is concave in consumption, $u_{cc} < 0$, therefore the RHS of equation (4.33) is negative. Equation (4.33) implies that the rate of growth of consumption is decreasing in the growth rate of pollution emissions, $\dot{P}$, abatement

[60] The derivation of equations (4.33) and (4.34) are offered in the appendix.

taxes, t, and the discount rate, ρ. Conversely, consumption is growing with return on investments, which is defined as $Y/(\eta \cdot N)$ (i.e., the second term on the RHS of (4.33) because $\psi < 0$), and emission intensities, Ω.[61]

The growth rate in (4.33) applies to the number of designs, N, output Y, and consumption, C. To see this, the budget constraint from (4.2) can be rewritten as

$$\begin{aligned} C &= Y - X - \left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right)\cdot X - \eta\cdot\gamma\cdot N \\ &= (1-\alpha)\cdot Y\left[1+\alpha(1-\tau)\right] - \eta\cdot\gamma\cdot N, \end{aligned} \tag{4.35}$$

where γ denote the growth rate from (4.33) and $\dot{N}/N = \gamma \Rightarrow \dot{N}\cdot\eta = \gamma\cdot N\cdot\eta$. If we substitute (4.33) for γ into (4.35) and simplify then we derive

$$C = \left(\frac{N}{\sigma-1}\right)\left\{\frac{Y}{N}\cdot\left(\psi_1\cdot(\sigma-1)+\psi_2\cdot\eta\right)+\eta\rho+\left(\frac{\alpha}{1-\tau}\right)\Omega\right\}. \tag{4.36}$$

Equation (4.36) implies that for fixed L and τ, C, N, and Y grow at the same rate γ.[62]

Equation (4.34) implies that the rate of growth of taxes is increasing with the discount rate, the growth rate of consumption, and the growth rate of pollution. Conversely, (4.34) implies that the tax growth rate is decreasing with the public's willingness-to-accept (WTA) as compensation for environmental damages. The public's WTA is captured in the first term of the RHS of (4.34). Note that the WTA term is similar to the Bergson-Samuelson rule for the optimal provision of a pure public good. In other words, if we specified utility as a function of environmental quality (a pure public good) instead of pollution (a pure public bad) then this term

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[61] It is costly to abate pollution, especially dirtier (or more intensive) types of pollution. Abatement efforts come at a cost then to consumption, so allowing for intensive emissions increases consumption over time.

[62] The derivation of (4.36) is listed in the appendix. σ denotes the elasticity of utility for consumption—we see this specification in the numerical analysis portion of this chapter. ψ_1 and ψ_2 both denote an equation of parameters.

would be the vertical sum of the public's willingness-to-pay for environmental quality.

It is not immediately obvious but the decentralized economy allocates fewer resources to intermediates (equation 4.15) and as a consequence ends up with a lower level of output (equation 4.16). The decentralized economy produces less intermediates because these goods are offered at the monopoly price $1/\alpha > 1$ (equation 4.13); whereas the social planner sets the price of these goods to their marginal cost. Since the intermediates are an ordinary good (downward-sloping demand curve) then more intermediates would be produced by the social planner, and consequently more output would be produced. In other words, there is an efficiency loss because of the monopoly power created by the patent system.

4.3.1 Steady-State

We will now explore the long-run behavior or *steady state* of the model based upon the optimal conditions (equations (4.33) and (4.34)). The steady state is defined as a trajectory in which the various quantities grow at a constant or zero rate. For ease of analysis we will assume that they are growing at a zero rate. When all the variables cease to grow then the optimal conditions reduce to:

$$\frac{Y}{\eta \cdot N} = \frac{1}{\psi} \cdot \left\{ \rho - \left(\frac{1}{\eta}\right) \cdot \left(\frac{\alpha}{1-\tau}\right) \cdot \Omega \cdot \varepsilon \cdot N^{\varepsilon - 1} \right\} \tag{4.37}$$

$$L \cdot \frac{u_P}{u_c} \cdot \frac{1}{\rho} = -\left(\frac{\alpha}{1-\tau}\right) \cdot \left(1 + \frac{\phi}{\rho}\right) \tag{4.38}$$

$$Lc = Y - X - \left(\frac{1}{\alpha}\right) \cdot \left(\frac{\tau}{1-\tau}\right) \cdot X \tag{4.39}$$

$$P = \left(\frac{1}{\phi}\right) \cdot \left\{ (\Omega - \tau) \cdot Y - \Omega \cdot N^{\varepsilon} \right\} \tag{4.40}$$

Equation (4.37) implies that the return on the investments is equal to a weighted value of innovations less the social discount rate.[63] The LHS of (4.37) is the socially optimal rate of return on investments. Equation (4.38) is the Bergson-Samuelson condition for the optimal provision of a public bad, which in this case is environmental pollution (Baumol and Oates, 1975; Kolstad, 2010). The RHS of (4.38) represents the negative sum of the ratio output elasticity of intermediates to the net abatement tax and the discounted value of nature's regenerative power.

Equation (4.39) is the budget constraint absent the growth rate of technological innovations. It implies that per capita consumption should equal national income less expenditures on intermediate goods, where the socially optimal amounts of income and intermediates is defined in equations (4.31) and (4.32) respectively.

Lastly, equation (4.40) implies that the long-run level of pollution is equal a weighted value of net pollution emissions from output less the reduction in pollution from clean-tech innovations.

4.3.2 Assumptions

In this section we will discuss our assumptions for the numerical analyses to be conducted in the next subsection. We will pay special attention to the steady state conditions since we are interested in the long-run relationship between pollution emissions, economic growth, and the growth of technological innovations. Unlike

[63] It should be noted that it is no trivial task to calculate the socially optimal discount rate and the optimal choice of investments in clean technologies is sensitive to the magnitude of the discount rate (Baumol, 1968).

Barro and Sala-i-Martin (2004), our model displays transitional dynamics (or short-run trajectories) because growth rate of pollution enters the equation of motion for consumption. We will, however, concentrate on the steady-state or long-run economic growth pollution relationship.

In order to conduct the numerical analysis we need to specify the functional form of utility. Following Chimeli and Braden (2005), we will base our numerical results on the following functional form:

$$u(c,E) = \sigma \cdot \ln(c) - (1-\sigma) \cdot \ln(P) \tag{4.41}$$

Equation (4.41) is a specification of the household's inter-temporal utility function that satisfies all the conditions specified in equation (4.1).[64] Similar to Chimeli and Braden (2005) we will assume that $\sigma = 0.8$. This implies that elasticity of utility with respect to pollution is -0.2; i.e., the public receives disutility from pollution. Further, we set the output elasticity of intermediates $\alpha = 1/3$, which is fairly standard in past literature and empirically valid.[65]

Following Chimeli and Braden (2005) we set the discount rate to $\rho = 0.02$. Following Brock and Taylor (2004) we assume the baseline emission intensity is fixed to $\Omega = 1$. For ease of analysis we assume a constant pollution tax rate of $\tau = 0.05$; we will also experiment with different fixed rates of the pollution tax to see its long-run effect on the economy and pollution levels.[66] We initially set the R&D cost parameter to $\eta = 20$; however, again we will conduct a sensitivity analysis based on

[64] Technically this does not satisfy all the conditions because with this specification $U_{cP} = 0$ so the equation of motion term for pollution drops out of the optimal consumption growth rate (4.33).
[65] This parameter implies that the capital share of aggregate production is one-third, which is approximately true into the U.S. (Cooley, 1995).
[66] A constant pollution tax may seem overly strict, but Vogan (1996) finds that pollution abatement and control has stayed relatively fixed between 1.7 and 1.8% of GDP since the mid-1970s.

different values of the R&D cost.[67] The returns to scale parameter on new technologies is initially set to $\varepsilon = 1.5$, but we will also experiment with different values of this parameter for a sensitivity analysis. We initially set the productivity parameter to $A = 0.75$, but will adjust this figure for a sensitivity analysis. Nature's regenerative ability, ϕ, is initially set to 0.001 so that there is a very small effect on future pollution emissions; in other words, assuming a very small value of ϕ is almost equivalent to assuming the pollutant is a flow variable.[68] Finally, we set the initial values of output, new design, and consumption to $Y(0) = 10{,}000$, $N(0) = 275$, and $C(0) = 6{,}000$, respectively.[69]

The initial values for output, Y, and new designs, N, may seem somewhat arbitrary, but according to a National Science Foundation report, R&D expenditures represented approximately 2.79% of GDP in 1999 (Payson, 1999). Our initial values predict that the number of new innovations represents 2.75% of output or GDP. Our model predicts that the rate of growth of output and new innovations is the same. This assumption is not exactly correct given the empirical data displayed in Figure 4.3, but the growth rates are very similar.

4.3.3 Numerical Analysis

Based upon our assumptions in section 4.3.2 we now examine the long-run growth paths of national income (output), pollution emissions, and pollution intensities based

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[67] This value was chosen after several initial pre-trials of our program.

[68] If ϕ is a relatively large value then nature has the ability to filter out the previous periods emissions, which implies that the pollutant is a stock variable. Therefore, we can approximately differentiate between a stock or flow variable by specifying a large or small value of nature's regenerative ability.

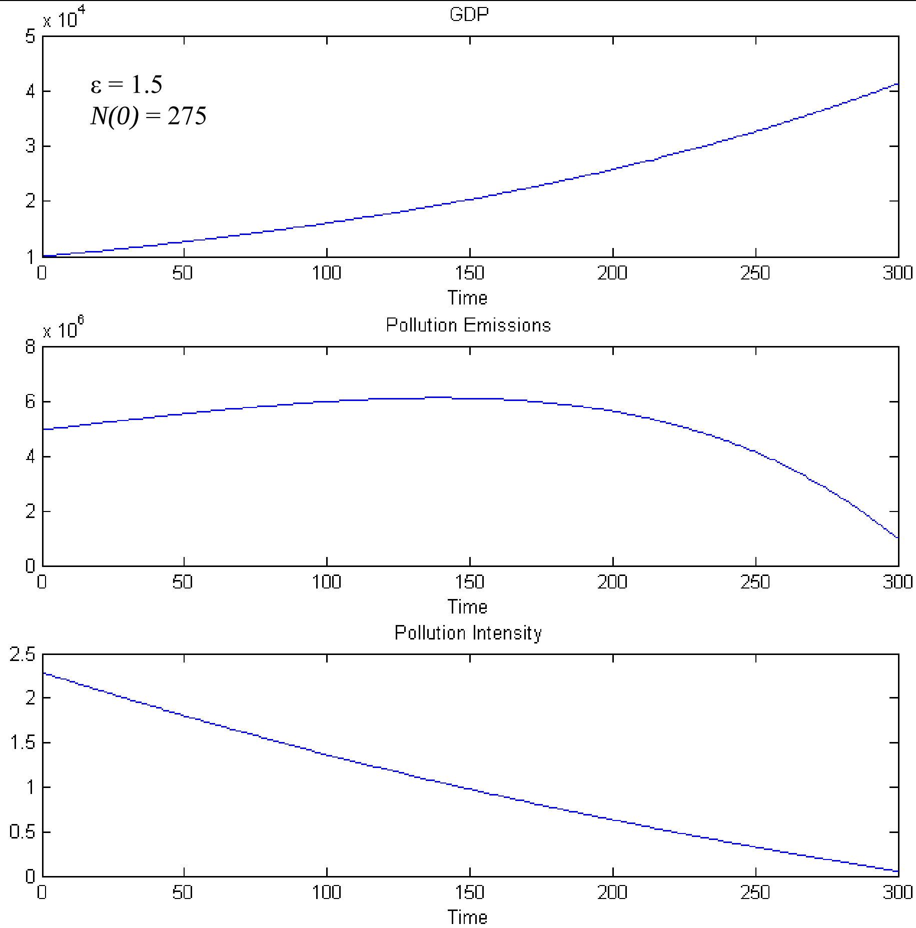
[69] 6,000 was chosen as the initial amount of consumption because consumption represented approximately 60% of US GDP in the 1960s; although, this really is not important to our analysis as we are analyzing GDP and pollution emissions.

upon our numerical analysis of the steady-state conditions in equations (4.37) through (4.40). Figure 4.5 represents the baseline to compare against the other simulations.

In Figure 4.5 we make all the assumptions outlined in previous subsection. As predicted by the EKC hypothesis, we find the familiar inverted-U shaped relationship as displayed by the second panel in Figure 4.5. The pollution emissions and pollution intensity curves also look very similar to the empirical curves provided in Figures 4.1 and 4.2.[70] As discussed in section 4.2.5, the inverted-U shaped relationship in the second panel is drawn from the assumption of increasing returns to scale (IRS) of private abatement efforts (i.e., new clean technologies), which is similar to Andreoni and Levinson's (1998) argument.

[70] An arbitrary value of 300 was chosen for the time component. This does not indicate 300 years; a better interpretation would be 300 months, in which case the period would be a 25 year time horizon.

Figure 4.5. Baseline GDP, Pollution Emissions, and Emission Intensity



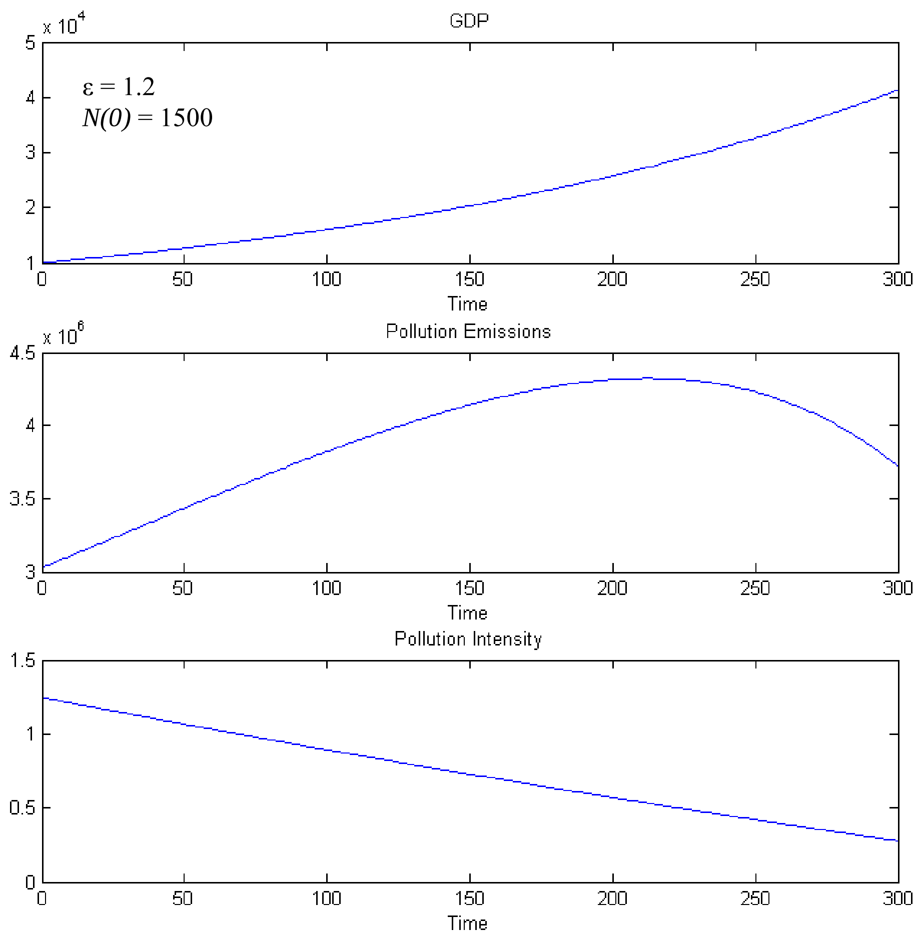
For a sensitivity analysis we reduce the returns-to-scale parameter, ε, on new innovations since Figure 4.5 is based on the IRS assumption. The new projections are presented in the Figure 4.6. Notice that a decrease in the parameter by 20% requires a nearly 450% increase in the initial number of innovations (from 275 to 1500) to derive the inverted-U shaped relationship.[71] For any initial number less than 1400 pollution emissions exhibit a monotonically increasing trend—a relationship that is not consistent with the empirical relationship found in Figure 4.1. Since this is not consistent with the empirical data it implies that innovations (at least for our model) must exhibit IRS. Further, an initial value of 1500 innovations implies 15% of output

[71] Note that an increase in the initial number of innovations is equivalent to a larger number of innovations in general over time because innovations and output are growing at the same rate.

is dedicated to new innovations which seems inconsistent with our findings of total aggregate R&D expenditures which were between 1.7% and 1.8% of GDP over the past few decades.

With the assumption of constant returns to scale of new innovations, pollution emissions increase monotonically, which again is not consistent with the empirical data (refer to Figure 4.1). Thus, the IRS assumption with private innovations is essential (in our analysis) to the inverted-U shaped relationship.[72]

Figure 4.6. Reduced Returns to Scale Parameter on Private Abatement



[72] This is consistent with Andreoni and Levinson (1998), Brock and Taylor (2004), Chimeli and Braden (2005), and Criado, et. al (2009).

An increase in the constant pollution tax, τ, requires less innovations to derive the purported EKC relationship. This relationship can be found in the appendix in Figure A.4.1. Given the baseline returns-to-scale parameter of 1.5, a tax rate increase of 100% (0.05 to 0.1) requires 40% less initial innovations (275 to 165). This implies that an economy with higher public abatement efforts requires less private abatement efforts to achieve a reduction in long-run pollution emissions. In an additional simulation (not shown) we reduced the returns-to-scale parameter to 1.2 and increased the tax rate to 0.1. To derive the EKC relationship, it required 1200 (or 12% of GDP) innovations, which again does not seem consistent with the empirical data (refer to Figure 4.3).

An increase in nature's regenerative ability, ϕ, requires less initial innovations to derive the EKC relationship. Figure A.4.2 shows that increase in nature's regenerative parameter by 4900% increase (0.001 to 0.05) leads to a 9% decrease in initial innovations (275 to 250). We experimented with higher values of the regenerative parameter and got similar results (not shown). Thus, a very large increase in nature's regenerative ability only leads to a small change in the number of innovations required for the EKC. In other words, pollution emissions seem very inelastic to large changes in the regenerative parameter. Intuitively, this occurs because the current emissions from output outweigh the nature's ability to regenerate itself from the proceeding period's emissions.

If we increase the emission intensity parameter, Ω, we obtain a monotonically decreasing relationship between economic growth and pollution emissions as shown in Figure A.4.3 in the appendix. An increase in pollution intensity leads to a huge increase in pollution emissions (compared to the baseline in Figure 4.5.); this stems from the fact that the increased pollution intensity also leads to an increase in Social Planner's optimal growth rate of consumption which in turn leads to a growth in output. Intuitively, this increase in output occurs because it is costly to abate pollution emissions, particularly intensive emissions; e.g., dirtier emissions imply that less abatement effort is being exerted.[73]

We experimented with the productivity parameter, A, to see its effect on total output and pollution emissions. The results for a reduction in the parameter are listed in the appendix in Figure A.4.4. A reduction of the parameter by 53% (from 0.75 to 0.35) results in pollution emissions monotonically decreasing over time. The reduction in pollution emissions however is driven by the reduction in output over time, and results in pollution intensities increasing over time. Conversely, an increase of the productivity parameter by 21% (from 0.75 to 0.95) leads to slow but steadily increasing output levels and monotonically decreasing pollution emissions levels (not shown).

We also experimented with the fixed R&D cost parameter, η. Intuitively, a decrease in R&D costs requires fewer initial new innovations to derive the EKC as listed in Figure A.4.6 in the appendix. Fewer initial innovations are needed because it is cheaper to conduct R&D and therefore more innovations enter the economy over time. The reduction in R&D costs also leads to higher levels of output over time. On

[73] We also experimented with a slight increase in the emission intensity (1 to 1.2) and a decrease in the returns-to-scale (1.5 to 1.2). In order to derive the inverted-U shaped relationship it requires an initial number of innovations to equal to 350 as shown in Figure A.4.5. These parameter specifications cause the growth-pollution relationship to increase slowly at first and then finally we see the inverted-U shaped relationship later in the time horizon.

the other hand, if we increase the parameter then output decreases over time and consequently pollution emissions decrease as well. With our model, any amount of R&D costs larger than the baseline assumption (i.e., $\eta > 20$) results in a decrease of output and consequently a decrease in pollution levels as displayed in A.4.7 in the appendix. This occurs because the optimal return on investments (the last two terms on the RHS equation (4.33)) is less than the discount rate; therefore the optimal rate of growth for output is decreasing over time.

Finally, a decrease in the parameter for the elasticity of utility from consumption, σ, also has an effect on pollution emissions over time. If we decrease the parameter by 25% (from 0.8 to 0.6) then we have to increase the initial number of innovations by 9.1% (275 to 300) to derive the EKC. Intuitively, this occurs because the household receives less utility from consumption (or more disutility from pollution) which slows the growth rate of consumption, output, and innovation. Since innovation slows it takes more new clean technologies to reduce pollution emissions over time. This relationship is displayed in Figure A.4.8. We experimented with lower values of the parameter (not shown) and discovered a similar pattern; i.e., a decrease in the utility of consumption requires a larger number clean technologies to reduce pollution emissions over time. Additionally, we found that an increase in the parameter required fewer innovations to derive the EKC.

4.4 Conclusions and Limitations

Based on our theoretical model we were able to show, consistent with the EKC hypothesis, that pollution emissions first rise and then fall as output expanded over time. Our results in the numerical analysis section showed that this inverted-U shape for pollution emissions was contingent upon the increasing returns to scale assumption on the clean-tech innovations (consistent with Andreoni and Levinson, 1998). Additionally, we discovered that as the returns-to-scale parameter, ε, approached one (or constant returns to scale) then the number of clean-tech innovations needed to observe the EKC must increase to levels that appear to be inconsistent with empirical observations. If innovations demonstrated constant returns to scale, then pollution emissions would increase monotonically over time, which again is inconsistent with empirical observations (see Figures 4.1 and 4.2).

For a sensitivity analysis we manipulated several of the parameters within the model to test for robustness of the inverted-U shape of pollution emissions. We found that an increase in public abatement efforts (as reflected in the abatement tax, τ) requires less clean-tech innovations over time to derive the EKC. Further, emissions seemed to be inelastic towards nature's regenerative ability parameter, ϕ. With an increase in emission intensity, Ω, we found the counterintuitive result that emissions were monotonically decreasing over time (instead of the baseline EKC shape). This result stemmed from the fact that the growth rate of consumption is increasing in emission intensity (see footnote 61 for an explanation) and innovations are growing at the same rate of consumption. Therefore, an increase in the growth rate leads to an increase in clean-tech innovations which further drive down pollution emission levels.

Further, a reduction in the productivity parameter, A, led to monotonically decreasing pollution emissions because output and innovations are decreasing over time. Conversely, an increase in the productivity parameter led to an increase in output and monotonically decreasing pollution emissions. The latter of the two seems more consistent with the empirical data. We discovered that our results are sensitive to the assumed value of R&D costs, η. If the cost exceeds a certain threshold then the discount rate exceeds return on investments and the growth rate of consumption is decreasing over time, which implies that output and innovations are decreasing as well (a result which is not consistent with the empirical observations in subsection 4.1.3). Lastly, a decrease in the elasticity of utility from consumption requires more clean technologies to derive the EKC and vice versa.

Unlike Chimeli and Braden (2005) our results imply that socio-economic policies that promote technological innovation and remove barriers to technical adoption could in and of themselves improve environmental quality (by reducing pollution emissions). Further, our analysis showed that if clean-tech innovations are characterized by increasing returns to scale, then private abatement efforts eventually overshadow public abatement efforts. This implies that in the long run policies aimed at supporting clean-tech R&D could be a more efficient use of resources then investments in public abatement efforts. A redirection of the government's resources is quite simple in the context of this model; e.g., instead of using abatement tax revenues to finance clean-up efforts, the government could simply shift those revenues to clean-tech R&D.

Finally as outlined in the introduction, since we assumed that pollution is a public bad we were able to derive the Bergson-Samuelson rule for the optimal provision of a public good (equation 4.38). Based on our baseline assumptions outlined in the previous section, we estimate that the optimal expenditures on pollution abatement to be 0.3684. This implies that households would be willing to accept roughly 37 cents of every dollar as compensation for producers generating pollution emissions. This result, for example, suggests that households would be willing to accept around a 37% decrease in their utility bills as compensation for pollution emissions resulting from electricity power generation.

Our model suffers from several limitations. One of the limitations is outlined in the previous paragraph. It would be an interesting exercise to model redirecting the government's abatement revenues towards R&D. Unfortunately, to keep the model tractable, we had to make many simplifying assumptions, such as treating the growth rate of taxes as fixed. The socially optimal growth of taxes (equation 4.34) implies that the tax growth rate would be decreasing over time as clean-tech innovations drive down pollution levels over time. Therefore, it would be an interesting exercise to allow the time dependent taxes to enter the steady-state conditions. Another interesting exercise would be to *estimate* the structural model (the social planner's solution) as opposed to *simulating* the model. An estimation of the model would involve incorporating empirical data into the structural model and then estimating it statistically.

One arguable limitation is that our simulations are based upon the social planner's solution (i.e., the Pareto Optimal solution) instead of the decentralized economy's solution. It would be an interesting exercise for future research to compare the social planner simulations to the decentralized simulations.

Another limitation stemmed from the assumption of constant R&D costs; a more dynamic analysis may allow R&D costs to vary over time. Finally, this chapter was limited by the assumption of the functional form of utility. Although this assumption was consistent with the literature, more flexible and interesting functional forms may be available that perhaps would lend more realism to the analysis.

Lastly, this chapter was limited by the lack of computer programs to conduct such numerical analyses. The current program was written entirely by the authors using Matlab. Future research could be greatly benefited by other researchers allowing public access to their own individual computer programming codes.

4.5 Appendix

Derivation of the Rate of Return Function in Equation (4.27)

$$
\begin{aligned}
r &= \frac{1}{\eta}\cdot(1-\alpha)\cdot\alpha\cdot\left(\frac{Y}{N}\right)\\
&= \frac{1}{\eta}\cdot(1-\alpha)\cdot\alpha\cdot AL^{1-\alpha}X^{\alpha}N^{-\alpha}\\
&= \frac{1}{\eta}\cdot(1-\alpha)\cdot\alpha\cdot AL^{1-\alpha}N^{-\alpha}A^{\alpha/(1-\alpha)}\alpha^{2\alpha/(1-\alpha)}L^{\alpha}N^{\alpha}\\
&= \frac{1}{\eta}\cdot(1-\alpha)\cdot\alpha\cdot LA^{1/(1-\alpha)}\alpha^{2\alpha/(1-\alpha)}\\
&= \frac{1}{\eta}\cdot\left(\frac{1-\alpha}{\alpha}\right)\cdot\alpha^{2}\cdot LA^{1/(1-\alpha)}\alpha^{2\alpha/(1-\alpha)}\\
&= \left(\frac{L}{\eta}\right)\cdot\left(\frac{1-\alpha}{\alpha}\right)\cdot A^{1/(1-\alpha)}\alpha^{2/(1-\alpha)}
\end{aligned}
\tag{A.1}
$$

Derivation of the Budget in (4.29)

$$
\begin{aligned}
&\frac{d(assets)}{dt} = wL + r\cdot(assets) - Lc\\
&\eta\cdot\dot{N} = (1-\alpha)Y + r\cdot(\eta N) - Lc\\
&\eta\cdot\dot{N} = (1-\alpha)Y + \alpha(1-\alpha)(1-\tau)Y - Lc\\
&\eta\cdot\dot{N} = Y - \alpha Y + (\alpha-\alpha^{2})(1-\tau)Y - Lc\\
&\eta\cdot\dot{N} = Y - \alpha Y + \alpha(1-\tau)Y - \alpha^{2}(1-\tau)Y - Lc\\
&\eta\cdot\dot{N} = Y - \alpha Y + \alpha Y - \alpha\tau Y - X - Lc\\
&\eta\cdot\dot{N} = Y - \alpha\tau Y - X - Lc\\
&\eta\cdot\dot{N} = Y - X - \alpha\tau Y\cdot\left(\frac{\alpha}{\alpha}\right)\cdot\left(\frac{1-\tau}{1-\tau}\right) - Lc\\
&\eta\cdot\dot{N} = Y - X - \alpha^{2}(1-\tau)Y\cdot\left(\frac{1}{\alpha}\right)\cdot\left(\frac{\tau}{1-\tau}\right) - Lc\\
&\eta\cdot\dot{N} = Y - X - \left(\frac{1}{\alpha}\right)\left(\frac{\tau}{1-\tau}\right)X - Lc
\end{aligned}
\tag{A.2}
$$

Derivation of H_τ from (4.31)

$$
\begin{aligned}
&v_1\left(\frac{1}{\eta}\right)\left\{-\left(\frac{1}{\alpha}\right)\frac{1}{(1-\tau)}X-\left(\frac{1}{\alpha}\right)\frac{\tau}{(1-\tau)^2}X\right\}+v_2Y=0\\
&-v_1\left(\frac{1}{\eta}\right)\left\{\left(\frac{1}{\alpha}\right)\frac{\tau}{(1-\tau)}X\left[\frac{1}{\tau}+\frac{1}{(1-\tau)}\right]\right\}=v_2Y\\
&-v_1\left(\frac{1}{\eta}\right)\left\{\left(\frac{1}{\alpha}\right)\frac{\tau}{(1-\tau)}X\left[\frac{1}{\tau(1-\tau)}\right]\right\}=v_2Y\\
&-v_1\left(\frac{1}{\eta}\right)\left(\frac{1}{\alpha}\right)\frac{1}{(1-\tau)^2}\frac{X}{Y}=v_2.
\end{aligned}
\tag{A.3}
$$

Recall that $X=\alpha^2(1-\tau)Y$,

$$
\begin{aligned}
&-v_1\left(\frac{1}{\eta}\right)\left(\frac{1}{\alpha}\right)\frac{\alpha^2(1-\tau)}{(1-\tau)^2}\frac{Y}{Y}=v_2\\
&-v_1\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right)=v_2.
\end{aligned}
\tag{A.4}
$$

Derivation of H_x from (4.31)

$$v_1\left(\frac{1}{\eta}\right)\left\{\alpha\frac{Y}{X}-1-\left(\frac{1}{\alpha}\right)\left(\frac{\tau}{1-\tau}\right)\right\}+v_2\{\alpha(\Omega-\tau)\}\frac{Y}{X}=0$$

$$v_1\left(\frac{1}{\eta}\right)\left\{\frac{\alpha^2(1-\tau)(Y/X)-\alpha(1-\tau)-\tau}{\alpha(1-\tau)}\right\}-v_1\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right)\{\alpha(\Omega-\tau)\}\frac{Y}{X}=0$$

$$\left\{\frac{1-\alpha+\alpha\tau-\tau}{\alpha(1-\tau)}\right\}=\left(\frac{\alpha}{1-\tau}\right)\{\alpha(\Omega-\tau)\}\frac{Y}{X}$$

$$\left\{\frac{1-\alpha-(1-\alpha)\tau}{\alpha(1-\tau)}\right\}=\left(\frac{\alpha}{1-\tau}\right)\{\alpha(\Omega-\tau)\}\frac{Y}{X}$$

$$\left\{\frac{(1-\alpha)(1-\tau)}{\alpha(1-\tau)}\right\}=\left(\frac{\alpha}{1-\tau}\right)\{\alpha(\Omega-\tau)\}\frac{Y}{X}$$

$$\left(\frac{1-\alpha}{\alpha^3}\right)\left(\frac{1-\tau}{\Omega-\tau}\right)=AL^{1-\alpha}N^{1-\alpha}X^{\alpha-1}$$

$$X^{\alpha-1}=\left(\frac{1-\alpha}{\alpha^3}\right)\left(\frac{1-\tau}{\Omega-\tau}\right)A^{-1}L^{\alpha-1}N^{\alpha-1}$$

$$X=A^{1/(1-\alpha)}\left(\frac{\alpha^3}{1-\alpha}\right)^{1/(1-\alpha)}\left(\frac{\Omega-\tau}{1-\tau}\right)^{1/(1-\alpha)}LN. \tag{A.5}$$

Derivation of Equation (4.33)

$$\dot{v}_1=\left(\frac{\eta}{L}\right)u_c\left\{\frac{u_{cc}}{u_c}\dot{c}+\frac{u_{cP}}{u_c}\dot{P}-\frac{\dot{L}}{L}\right\} \tag{A.6}$$

LHS of (A.6) from the necessary conditions,

$$
\begin{aligned}
\dot{v}_1 &= -v_1\left(\frac{1}{\eta}\right)(1-\alpha)\frac{Y}{N} - v_2\left\{(\Omega-\tau)(1-\alpha)\frac{Y}{N} - \Omega\varepsilon N^{\varepsilon}\right\} \\
&\quad +(\rho-n)v_1 \\
&= -v_1\left(\frac{1}{\eta}\right)(1-\alpha)\frac{Y}{N} + v_1\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right)\left\{(\Omega-\tau)(1-\alpha)\frac{Y}{N} - \Omega\varepsilon N^{\varepsilon}\right\} \\
&\quad +(\rho-n)v_1 \\
&= \left(\frac{\eta}{L}\right)u_c\left(\frac{1}{\eta}\right)(1-\alpha)\frac{Y}{N} + \left(\frac{\eta}{L}\right)u_c\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right) \\
&\quad \cdot\left\{(\Omega-\tau)(1-\alpha)\frac{Y}{N} - \Omega\varepsilon N^{\varepsilon}\right\} + (\rho-n)\left(\frac{\eta}{L}\right)u_c.
\end{aligned}
\tag{A.7}
$$

Simplify (A.6) and (A.7),

$$
\begin{aligned}
&\left\{\frac{u_{cc}}{u_c}\dot{c} + \frac{u_{cP}}{u_c}\dot{P}\right\} = -\left(\frac{1}{\eta}\right)(1-\alpha)\frac{Y}{N} + \left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right) \\
&\cdot\left\{(\Omega-\tau)(1-\alpha)\frac{Y}{N} - \Omega\varepsilon N^{\varepsilon}\right\} \ +(\rho-n) \\
&\left\{\frac{u_{cc}}{u_c}\dot{c} + \frac{u_{cP}}{u_c}\dot{P}\right\} = \left(\frac{1}{\eta}\right)(1-\alpha)\frac{Y}{N}\left\{\left(\frac{\alpha}{1-\tau}\right)(\Omega-\tau) - 1\right\} \\
&-\left(\frac{\alpha}{1-\tau}\right)\left(\frac{1}{\eta}\right)\Omega\varepsilon N^{\varepsilon} + \rho \\
&\dot{c} = \frac{u_c}{u_{cc}}\left\{\psi\left(\frac{Y}{N}\right) - \left(\frac{\alpha}{1-\tau}\right)\left(\frac{1}{\eta}\right)\Omega\varepsilon N^{\varepsilon} + \rho - \frac{u_{cP}}{u_c}\dot{P}\right\} \\
&\dot{c} = \frac{u_c}{u_{cc}}\left\{\psi\cdot A^{1/(1-\alpha)}\left(\frac{\alpha^3}{1-\alpha}\right)^{\alpha/(1-\alpha)}\left(\frac{\Omega-\tau}{1-\tau}\right)^{\alpha/(1-\alpha)}\cdot L\right. \\
&\left.-\left(\frac{\alpha}{1-\tau}\right)\left(\frac{1}{\eta}\right)\Omega\varepsilon N^{\varepsilon} + \rho - \frac{u_{cP}}{u_c}\dot{P}\right\},
\end{aligned}
\tag{A.8}
$$

where $\psi = \left(\frac{1}{\eta}\right)(1-\alpha)\left\{\left(\frac{\alpha}{1-\tau}\right)(\Omega-\tau) - 1\right\}$.

Derivation of Equation(4.34)

$$-\dot{v}_1\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right)-v_1\left(\frac{1}{\eta}\right)\frac{\alpha}{(1-\tau)^2}\dot{\tau}=\dot{v}_2$$

$$-v_1\left\{\frac{u_{cc}}{u_c}\dot{c}+\frac{u_{cP}}{u_c}\dot{P}-n\right\}-v_1\left(\frac{1}{\eta}\right)\frac{\alpha}{(1-\tau)^2}\dot{\tau}=-u_E-(\phi+\rho-n)v_1\left(\frac{1}{\eta}\right)\left(\frac{\alpha}{1-\tau}\right) \tag{A.9}$$

$$\left\{\frac{u_{cc}}{u_c}\dot{c}+\frac{u_{cP}}{u_c}\dot{P}-n\right\}+\frac{\dot{\tau}}{(1-\tau)}=L\frac{u_P}{u_c}\left(\frac{\alpha}{1-\tau}\right)+(\phi+\rho-n)$$

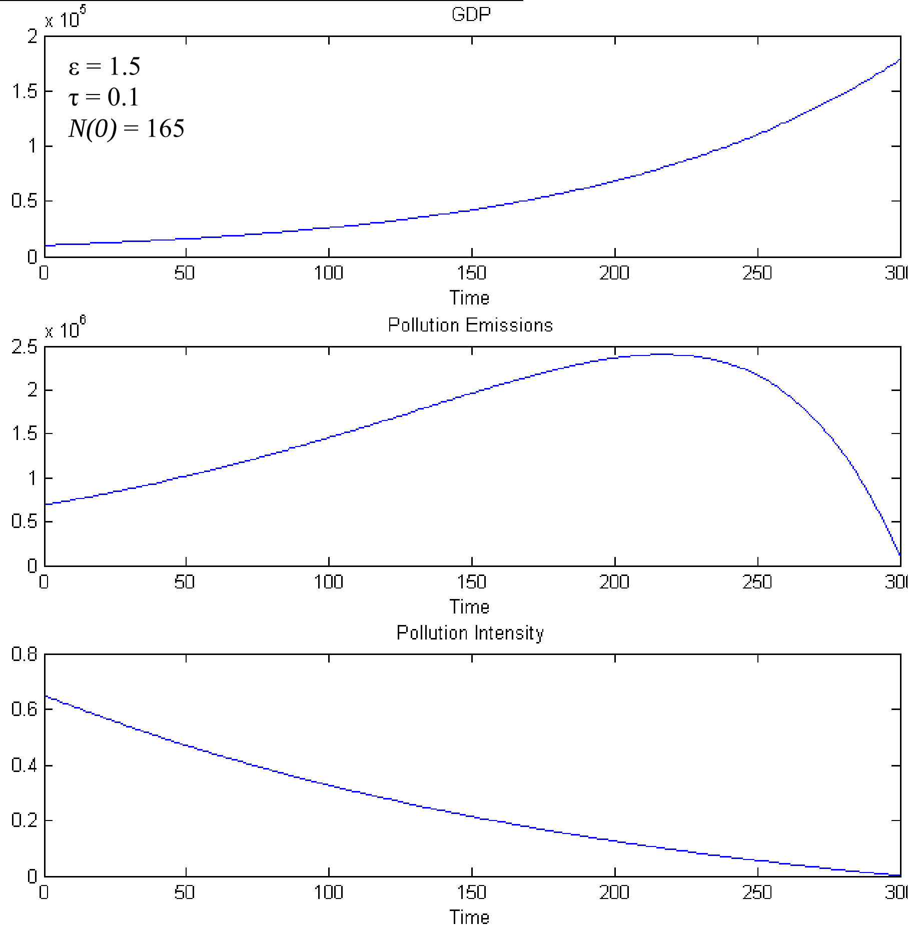
$$\dot{\tau}=(1-\tau)\left\{L\frac{u_P}{u_c}\left(\frac{\alpha}{1-\tau}\right)+\phi+\rho-\frac{u_{cc}}{u_c}\dot{c}-\frac{u_{cP}}{u_c}\dot{P}\right\}$$

Derivation of Equation (4.36)

$$
\begin{aligned}
C &= \psi_1 \cdot Y - \eta \cdot N \cdot \left(\frac{1}{\sigma - 1}\right) \cdot \left\{ \frac{u_{cP}}{u_c} \cdot \dot{P} - \rho \right. \\
&\quad \left. - \left(\frac{1}{\eta}\right) \cdot \psi_2 \cdot \left(\frac{Y}{N}\right) - \left(\frac{1}{\eta}\right) \cdot \left(\frac{\alpha}{1-\tau}\right) \cdot \Omega \right\} \\
&= \left(\frac{N}{\sigma - 1}\right) \left\{ \psi_1 \cdot \left(\frac{Y}{N}\right) \cdot (\sigma - 1) - \eta \cdot \frac{u_{cP}}{u_c} \cdot \dot{P} + \eta\rho \right. \qquad \text{(A.10)} \\
&\quad \left. + \psi_2 \cdot \eta \left(\frac{Y}{N}\right) + \left(\frac{\alpha}{1-\tau}\right) \cdot \Omega \right\} \\
C &= \left(\frac{N}{\sigma - 1}\right) \left\{ \left(\frac{Y}{N}\right) \left[\psi_1 \cdot (\sigma - 1) + \psi_2 \cdot \eta\right] + \eta\rho + \left(\frac{\alpha}{1-\tau}\right) \cdot \Omega \right\}
\end{aligned}
$$

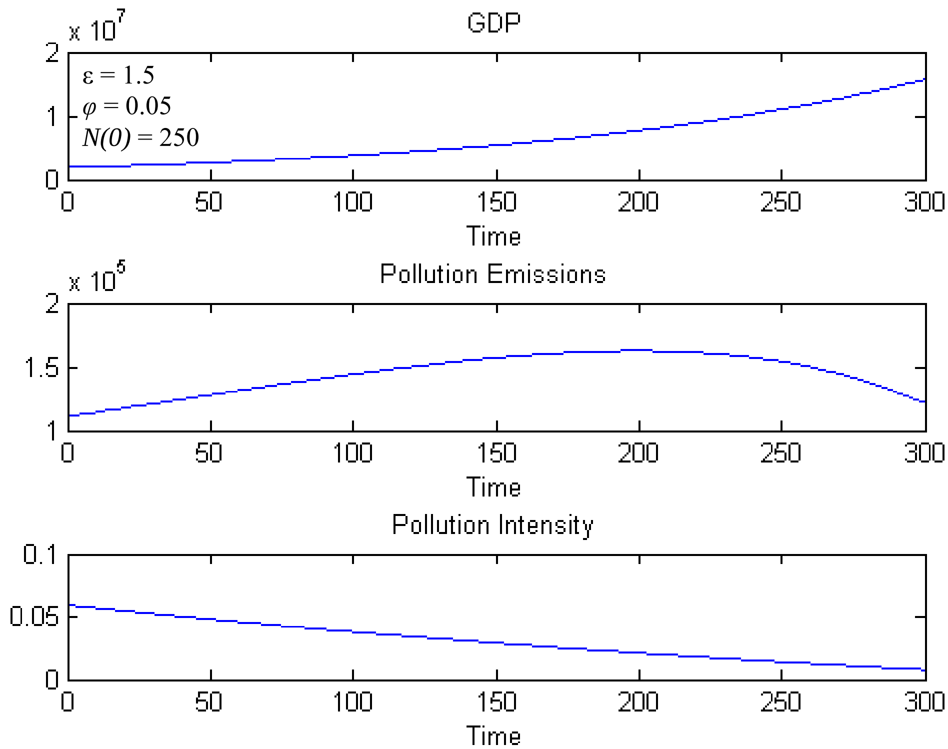
Increase in Constant Pollution Tax

<u>Figure A.4.1. Increase in Pollution Tax</u>



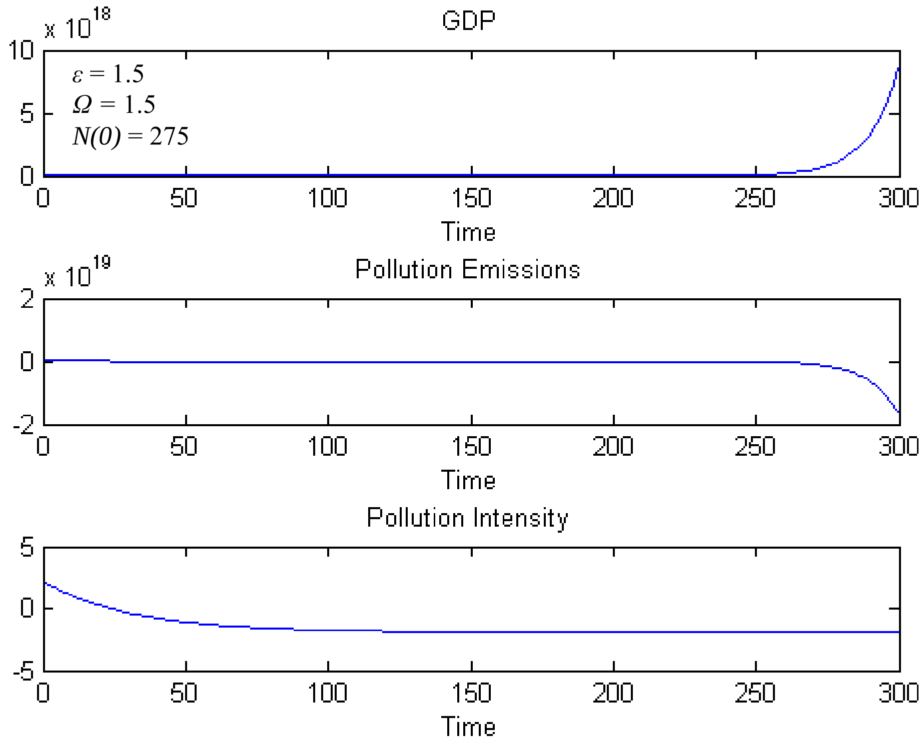
Increase in Nature's Regenerative Ability Parameter

<u>Figure A.4.2. Increase in Nature's Regenerative Parameter</u>



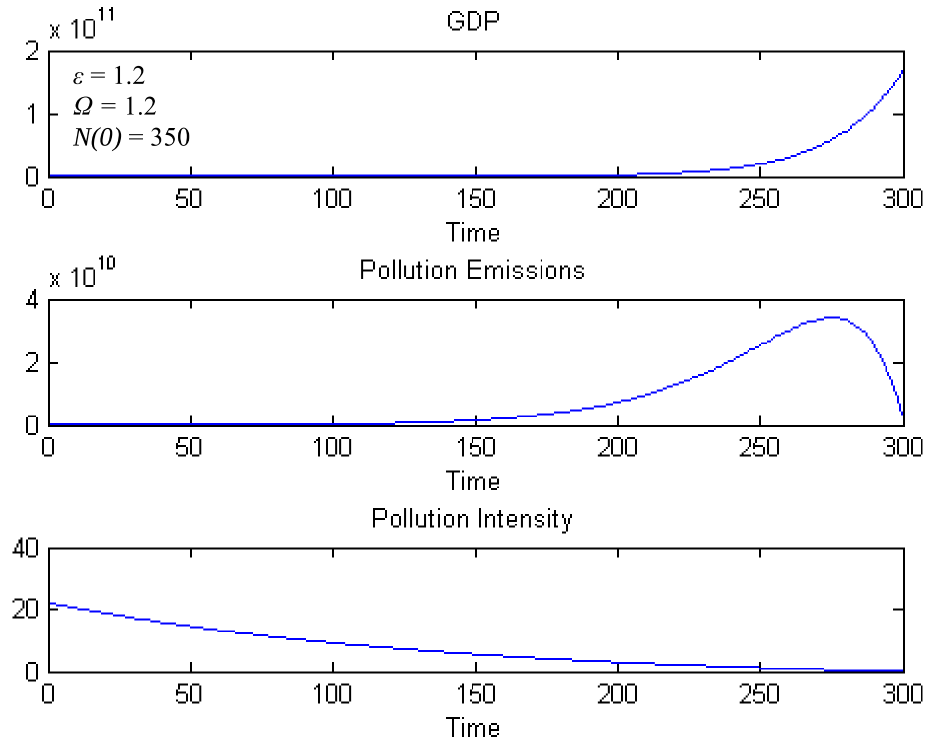
Increase in Emission Intensity

<u>Figure A.4.3. Increase in Emission Intensity Parameter</u>



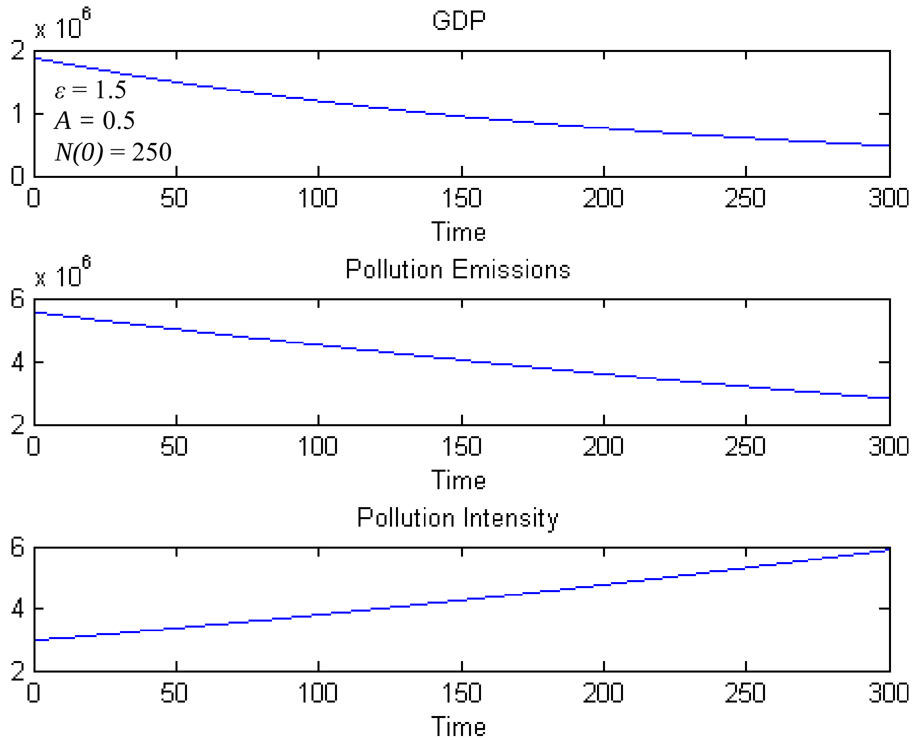
Increase in Emission Intensity and Decrease with RTS Parameter

Figure A.4.4. Slight Increase in Emission Intensity and Decrease with Returns-to-Scale Parameter



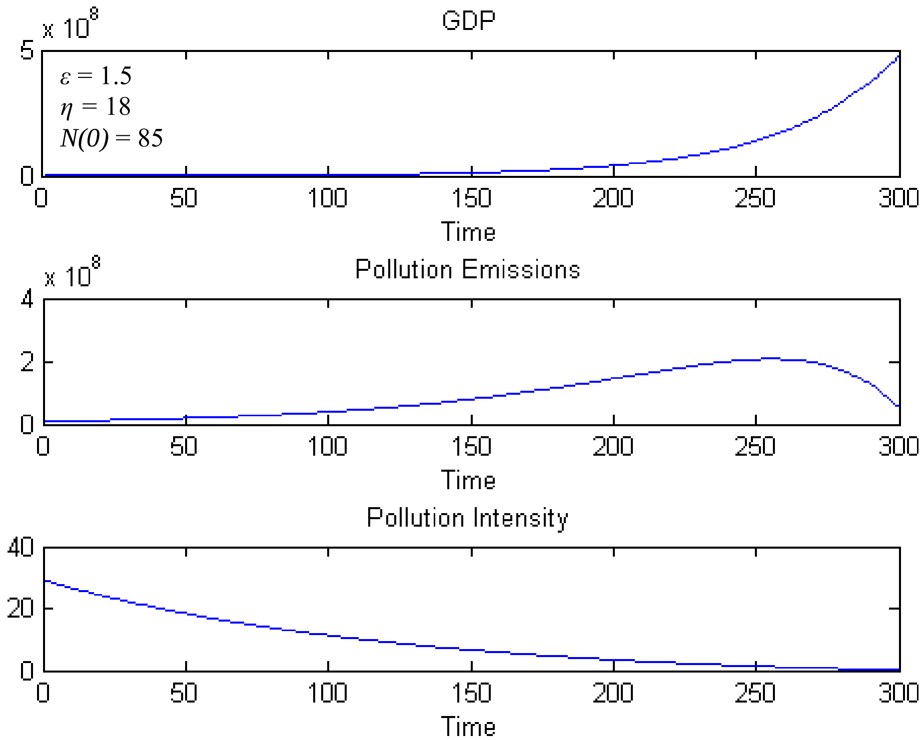
Decrease in Productivity Parameter

Figure A.4.5. Decrease in the Productivity Parameter



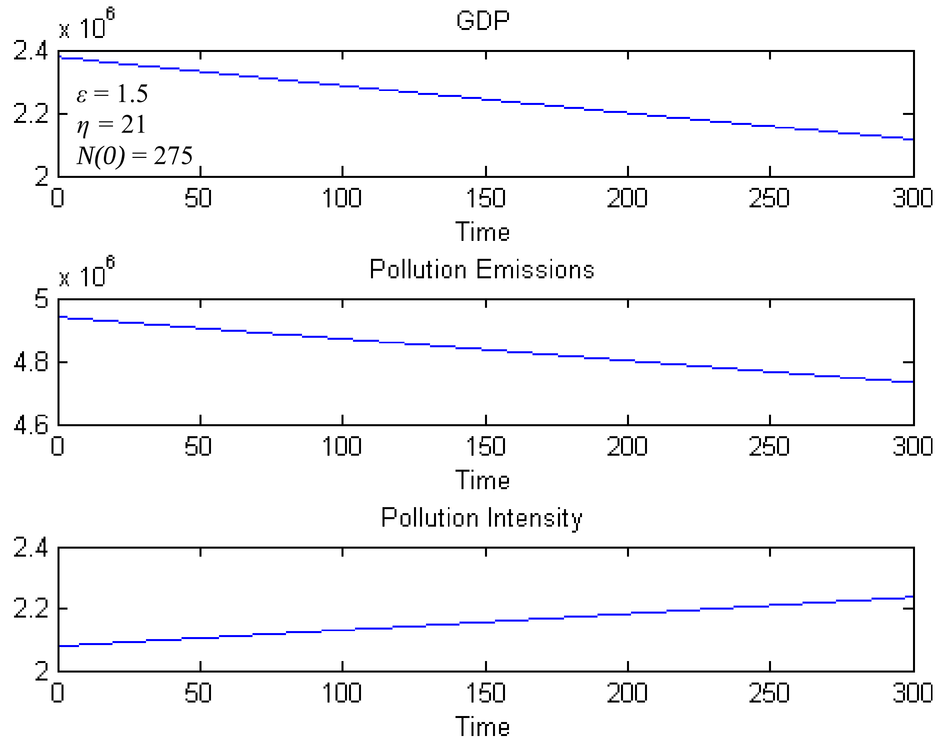
Decrease in R&D Costs

Figure A.4.6. Decrease in R&D Costs



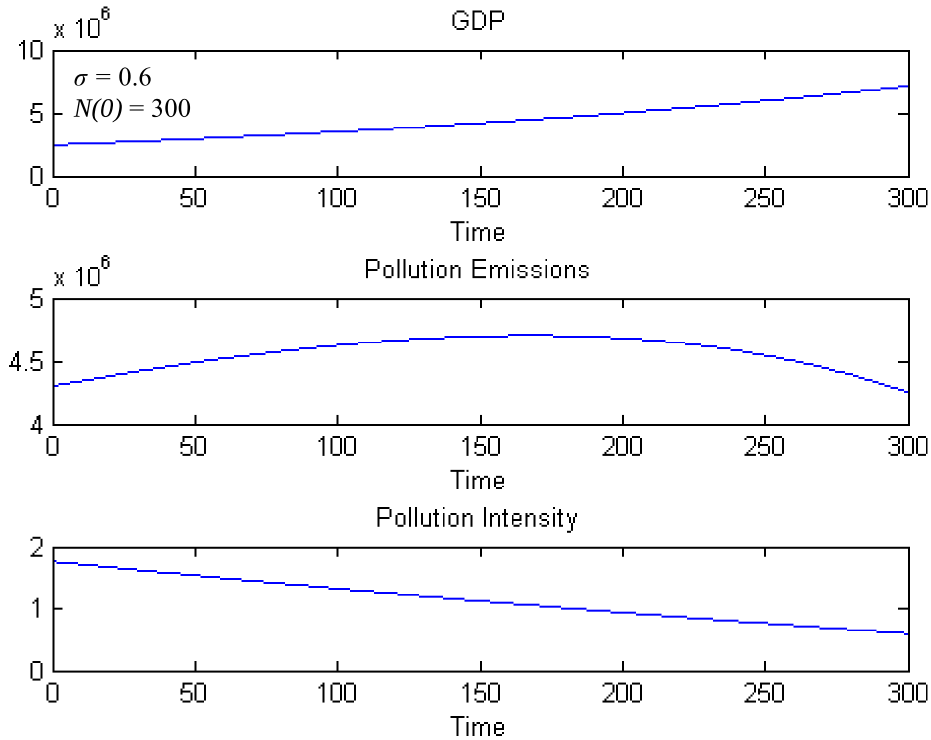
Increase in R&D Costs

Figure A.4.7. Increase in R&D Costs



Decrease in the Utility from Consumption

Figure A.4.8. Decrease in the Utility from Consumption



Chapter 5. Conclusions and Limitations

5.1 Conclusions

The objectives of this dissertation were three-fold: 1) to offer a critical examination of the current literature to take stock of where the EKC hypothesis is today; 2) to examine the spatial-temporal dependence within the empirical EKC literature; and 3) to expand the current theoretical EKC literature by modeling technological innovation as the driving force in the reduction of pollution emissions. We explored the first goal in the second chapter of this dissertation. In Chapter 2 we discovered that the empirical literature is lacking sufficient investigations into spatial dependence within the economic growth and pollution data. Thus, past studies may suffer from biased estimates of the economic growth-pollution relationship by not accounting for potential spatial dependence in the pollution indicator data.

We expanded the literature in this regard by offering an estimation procedure in Chapter 3 that controls for spatial and temporal dependence within the economic growth-pollution relationship. Since GDP is generally characterized by a unit root, we have reason to believe that it temporally dependent. We are less sure of the spatial dependence within GDP but intuition leads us to believe that national income contains spatial spillovers within the 48 contiguous states of the U.S. Further, we have reason to believe that several pollution emissions are characterized by both spatial and temporal dependence. This spatial-temporal dependence should be especially apparent in stock pollutants such as wastes or CO_2 emissions.

Our analysis contained estimates of CO_2 emissions, not actual concentration readings themselves (or atmospheric pollution); nevertheless, we could still make the argument that the underlying economic process driving the demand for energy is spatially and temporally dependent. This demand for energy in turn leads to an increase in the combustion of dirty fossil-fuels which in turn leads to an increase in pollution emissions, *ceteris paribus*. Having controlled for the spatial-temporal aspects of the data, we still find evidence of the inverted-U shaped relationship (within the 48 contiguous states of the US) espoused by Grossman and Krueger (1991) in their seminal work on this topic.

Despite our findings with the empirical literature, our empirical approach as identified in our critique in Chapter 2, only contains a reduced-form examination of the relationship between economic growth and pollution. In other words, we made new and unique contributions to the EKC literature with respect to empirical modeling and estimation techniques without still fully understanding the true theoretical relationship. To make up for this shortcoming we offered a theoretical model in Chapter 4 which accounts for technological growth within a theoretical closed-economy.

We make the argument that clean-tech innovation, driven by economic growth and concerns over environmental quality, is the true driver for reductions in pollution emissions. We discovered that pollution, a public bad, is reduced by clean-tech innovations and the shape of the pollution emissions path is driven by the returns to scale of those clean-tech innovations. The shape of the pollution emissions path and how quickly it converges to its long-term path depends on the elasticity of disutility from pollution, R&D costs, and the returns to scale of new innovations. If the innovations demonstrated increasing returns to scale, we found the traditional inverted-U shaped relationship, even if nature's regenerative ability is quite small. We found that when R&D costs cross a certain threshold (i.e., are too large), outputs decrease over time. However, because output is decreasing, pollution emissions still fell (an interesting result but not consistent with the empirical data of historic pollution emissions in the US). Finally, if pollution emissions are intense (dirty), we found counter-intuitively that those emissions would follow a monotonically decreasing path over time.

Thus, we have expanded the empirical and theoretical literature and in the process supported our own hypothesis that we would find the same inverted-U shaped relationship in our analyses. Mostly importantly, as Carson (2010) points out, the lasting contribution of our analysis is to change the conventional wisdom of economists, environmentalists, and policy-makers to believe that economic growth can actually be beneficial to the environment.

5.2 Limitations and Future Research

Our study suffers from several limitations which were outlined in the individual chapters (especially Chapters 3 and 4). Based upon our analyses, we believe that the main limitations within the literature can be categorized into two key areas: 1) there has been a severe lack of investigation into spatial dependence within the empirical literature; and 2) there have been insufficient investigations into the relationship between economic growth, technological growth, and pollution emissions. We overcame the first gap by offering our spatial-temporal panel data estimation scheme;

however, our analysis suffers from the fact that our CO_2 emissions data were based on estimated values, not actual atmospheric pollution. Our estimation scheme could be greatly enhanced by exploring actual atmospheric pollution levels. It would be especially interesting to see the results with a stock pollutant such as sulfur dioxide emissions. We believe that the spatial-temporal panel estimation scheme has tremendous potential to investigate most water pollutants as well because water pollutants are generally non-source point pollutants that are easily dispersed over wide geographic areas. For example, a pollutant in a river basin may not be traced back to a particular source and it may be carried over several miles; i.e., there are spatial spillovers.

We overcame the second gap within the literature by offering a theoretical model which accounted for the growth of “clean” technologies over time. This model expands the current theoretical literature, but lacks the sophistication to explain both the growth and the *variance* of technologies over time. A promising area of research modeling endogenous growth is being carried out by Comin and Mulani (2006). These authors model technological growth by exploring both the vertical and horizontal innovation processes simultaneously (recall that our model was only composed of a horizontal innovation process). The details of Comin and Mulani’s (2006) work are beyond the scope of this dissertation, but their model does a better job of explaining the effect of technological growth on national income. Despite our model’s inability to explain the variance of technological growth we believe that our model at least captures the average effect of clean technologies on pollution emissions over time.

Finally, the last limitation of this research involves the lack of computer programs available for both the investigation of spatial econometrics and endogenous growth models. It would greatly enhance future research if researchers would place their code and programs on the Internet (or some other open forum) for other researchers to freely access.

Glossary

CADF: Cross-sectional Augmented Dickey Fuller

CDIAC: Carbon Dioxide Information Analysis Center

CDD: Cooling Degree Days

CML: Conditional Maximum Likelihood

CO_2: Carbon Dioxide

DOLS: Dynamic Ordinary Least Squares

EGM: Endogenous Growth Model

EKC: Environmental Kuznets Curve

EPA: Environmental Protection Agency

GDP: Gross Domestic Product

GMM: General Method of Moments

HDD: Heating Degree Days

IGCC: Integrated Gasification Combined Cycle

IPSHIN: Im, Pesaran, Shin Test

IRS: Increasing Returns to Scale

IV: Instrumental Variables

LM: Lagrange Multiplier

LSDV: Least Squares Dummy Variables

NAFTA: North American Free Trade Agreement

NO_x: Nitrogen Oxide

OLS: Ordinary Least Squares

OVB: Omitted Variable Bias

R&D: Research and Design

RHS: Right Hand Side

RTS: Returns to Scale

SFD: Spatial First-Difference Estimation

SFE: Spatial Fixed Effects Estimation

TFP: Total Factor Productivity

UMLE: Unconditional Maximum Likelihood Estimator

WTA: Willingness-to-Accept

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