# AN ABSTRACT OF THE THESIS OF

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Title: Using Country-Level Forest Coverage to Analyze the Existence of an Environmental Kuznets Curve

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This thesis seeks to analyze the relationship between economic growth and environmental quality, in this case measured by forest cover, and analyzes whether this relationship is consistent with an Environmental Kuznets Curve. Additionally the relationship between population density and forest cover was analyzed. A simple theoretical model is derived that describes a number of conditions under which the socially optimal growth path of forest cover may be consistent with an Environmental Kuznets Curve. This curve shows that, as income per capita increases, forest cover will initially decrease and, upon reaching a turning point, may eventually increase. A time series panel dataset consisting of 96 developing and developed countries, spanning from 1950-2010, was constructed from the FAOs Global Forest Resource Assessments. The empirical analysis included a number of explanatory variables, such as income per capita and population density, and other factors that could influence the growth path of forest cover. Results of the random effects estimations proved to be inconclusive after adjusting for the heteroskedasticity and autocorrelation present in the data. Evidence in favor of an Environmental Kuznets Curve, based on the results, is therefore limited but is not sufficient to support or refute its existence.

Using Country-Level Forest Coverage to Analyze the Existence of an Environmental Kuznets Curve

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Sam Franciscus Johannes Gulpen, Author

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## 1. Introduction

The Environmental Kuznets Curve (EKC) describes the possible relationship between economic development and environmental degradation, resembling Simon Kuznets' well-known hypothesis that as an economy develops income inequality will rise at first, but will start to decline after a certain income threshold is achieved (Kuznets, 1955). An EKC relationships exhibits an inverted U-shaped curve for environmental degradation following economic development, often measured as income per capita. The EKC hypothesizes that environmental degradation will initially increase with rising levels of income per capita and, upon reaching an income turning point, will start to decrease. In the case of environmental quality measures (as opposed to degradation measures), such as forest coverage, the EKC will be U-shaped, where forest cover will initially decrease with income growth and, upon reaching the income turning point, will start to increase.

Environmental degradation, or quality, can be measured in a many different ways. One of these indicators of environmental quality is the extent of forest coverage and its potential increase or decrease over time. Globally, forest coverage has been declining for decades. Between 1990 and 2000 the FAO (2010) estimated the net change in forest area to be -8.3 million hectares per year and between 2000 and 2010 the net change was estimated at -5.2 million hectares per year. While the decline in forest areas has slowed, forest areas have continued to decline. Large declines in forest areas have serious consequences for both the environment and economies that rely on forests. Forests are a valuable aspect of a wide range of environmental, economic and social services, and the continued loss of forests poses serious damages to countries and people all over the world. While forests provide many amenities such as inputs in many production processes, losses in forest areas can have far reaching consequences with regard to biodiversity losses, increased carbon emissions and soil degradation (UNEP, FAO and UNFF, 2009). The data presents a unique opportunity to assess the development of forest cover over time and between countries, and may offer some insights into the role that income, population density and other factors play in this development

This thesis sets out to analyze factors affecting change in forest cover over time and attempts to test the EKC hypothesis. In addition to the relationship between forest cover and income per capita, the relationship between forest cover and population density will be investigated. Some of the EKC literature has investigated the latter and found support for an EKC between indicators for environmental quality and population size or density. The literature assessing the merits of the EKC of forest-related environmental quality measures is less extensive than the literature that uses other indicators of environmental quality. The 60-year length of the panel dataset that is used in the empirical analysis covers a much longer time period than other studies that are restricted to shorter datasets, often caused by limited data availability.

This paper is organized as follows: Chapter 2 provides the literature review, introduces the general literature and discusses possible explanations of an EKC in the theoretical literature (2.1). Section 2.2 reviews some of the empirical literature and focuses on the empirical problems encountered. Section 2.3 discusses the literature that specifically looked at forest and forestry related environmental quality measures and the final section (2.4) describes the value of forests and causes of deforestation. Chapter 3 presents the theoretical model. Chapter 4 discusses the empirical approach (4.1) and concludes with a description of the data (4.2) and the process of removing outliers (4.3). Chapter 5 discusses the results and the choices between different specifications of estimations. Chapter 6 provides a synthesis of the results and discussion, followed by the conclusion in Chapter 7.

## 2. Literature Review

Economists Gene Grossman and Alan Krueger were the first to posit that there may be an inverted U-shaped relationship between income per capita and environmental quality (1991). The conclusions drawn in their work and later papers, stating that income growth would not necessarily lead to continued declines in environmental quality, was at odds with the view that economic development was the driving force of environmental degradation and that there are limits to growth, due to resource scarcity. As Carson (2010) points out, most of the discussion on the effects of growth on environmental quality was previously based on the I=PAT equation. This relationship states that the impact on environmental quality (I) is a function of the population size (P), income or affluence (A), and technology (T). In most of the economic growth literature, population and affluence were considered the main causes of environmental degradation. While the IPAT equation and the EKC are in a sense both looking at the same question (Are there limits to growth?), in most of the literature regarding the relationship between income and environmental quality, the IPAT equation is not referenced or discussed. Carson attributes this to the fact that the IPAT equation was mostly used by trade economists, while the initial works analyzing the relationship between income and environmental quality (later on called the EKC) were mainly conducted by environmental and resource economists.

The proponents of the IPAT equation argued that the combined growth in population, affluence and technology would have to be limited in order to preserve the environment (Ehrlich and Holdren, 1971), thus making sustainable growth impossible. Economists studying the EKC note that this isn’t necessarily the case based on three arguments. The first argument is based on the fact that technological progress, which was often considered a neutral component of the IPAT equation, can serve to offset the detrimental effects of rising population and affluence. The second argument is that the IPAT models do not include any behavioral response to highly detrimental environmental degradation (i.e. prices and policies cannot react to changing environmental conditions in IPAT models). The next section will discuss the theoretical foundation of the EKC literature and describes how behavioral responses can be incorporated in an economic growth model that investigates the relationship between economic development and environmental quality. The third counterargument is directed towards the empirical side of the IPAT literature that faces issues concerning the quantity and quality of data used in estimations (Carson, 2010). Unfortunately, this problem is often associated with the EKC literature as well (Stern, 2003).

**2.1 Theoretical Literature**

Grossman and Krueger (1991) were the first to propose a mechanism through which the EKC might be explained. They identify three effects that economic expansion can have on the environment: the scale, composition and technique effects. The scale effect is intuitive in the sense that as economies develop and income increases, the scale of production increases, causing pollution to increase and environmental quality to decrease. The composition effect emerges when countries specialize in markets in which they have a comparative advantage. This specialization might occur if international competition increases when trade barriers are lifted, as was the case after NAFTA (Grossman and Krueger, 1991; 1995). If this comparative advantage is driven by environmental policies, the prevailing industries in countries with, for example, strict pollution control will be those industries that are inherently less detrimental to the environment and emit less pollution. The technique effect is a change in production techniques that may have an effect on pollution. The pollution intensity of production is likely to change when production techniques change. Whether the pollution intensity increases or decreases, depends on the nature of the different techniques. However, the authors indicate there are two reasons to believe that newer techniques will have lower pollution intensities, especially in developing countries. The first states developing countries could adopt modern technologies from developed countries. These technologies are more likely to be less pollution intensive, because of growing global awareness to protect the environment. The second reason involves a growing desire, on the part of consumers, for a cleaner environment as income rises. Policy makers could potentially adapt more and better environmental protection legislation in respond to this growing desire for a clean environment. The combination of scale, composition and technique effects could predict a growth path of environmental quality that is consistent with the EKC relationship. The scale effect has an unambiguous negative effect on environmental quality. The composition effect is more ambiguous on a country-level basis, but is not likely to cause an overall increase in environmental quality. The technique effect is also ambiguous, but allows for the possibility of an increase in environmental quality (Carson, 2010). If a positive technique effect (less pollution intensive, or fewer resource depleting technologies) outweighs the scale and composition effects, as income increases, a curve might manifest that is consistent with the EKC relationship.

The composition effect described by Grossman and Krueger lends itself to a separate theory that has emerged as a possible explanation for an EKC. This explanation is often referred to as the “pollution haven hypothesis” and relies on the assumption that as international trade barriers are lifted, industries that are heavy polluters will relocate to countries that have weaker environmental protection or fewer incentives to clean up production processes. These countries are expected to be developing countries, thus providing a rationale for why lower income levels are associated with higher pollution or environmental degradation in an EKC (de Bruyn, 2000).

Some researchers have found fault with the fact that most theoretical EKC models do not incorporate a feedback loop between environmental degradation and production. Arrow et al. (1995) point out that many models unjustly incorporate income as an exogenous variable and that these models exclude the possibility that environmental degradation could have an effect on income. Copeland and Taylor (2003) affirm this statement and indicate that the endogeneity between income and pollution has been overlooked in most of the literature by implicitly or explicitly assuming one-good frameworks. Copeland and Taylor are the first to mathematically derive a “sources of growth model” which takes this endogeneity into account. The model examines the sources behind growth and identifies a dirty factor (capital accumulation), which stimulates growth in the dirty industry more than the clean industry, and a clean factor (human capital) which stimulates growth more in the clean industry than the dirty industry. Under the assumption that policy responses to pollution are exogenous, pollution will decrease monotonically as income increases when growth occurs through the accumulation of capital. Under endogenous policy responses, pollution may decrease with capital accumulation if the income elasticity of marginal damage is not too high.. If in early stages of development, economies grow mainly through the accumulation of capital and in later stages through the accumulation of human capital, an EKC may still arise, even if policy responses are relatively weak.

One of the first to create a theoretical model that supported the possibility of an EKC is López (1994). López makes a distinction between resources that affect utility through flow effects, like air quality, and resources that have both stock and flow effects, like deforestation and biomass (or stock of forests). For the latter, however, López assumes that the stock and flow effects do not affect utility directly. Instead, both the flow and stock of forests affect the production function, and therefore also income. For resources that only exhibit flow effects, López finds that when consumers exhibit non-homothetic preferences and the willingness to give up additional income for increased environmental quality (income elasticity of environmental quality) is sufficiently high, a U-shaped curve may emerge between income and environmental quality. This relationship depends on whether individual producers internalize the negative stock effect. If forest land is owned privately, for example, the owner has more incentive to conserve the stock of forest to maintain long term growth. This is also valid when internalization is induced by government policy or contractual obligations.

A number of papers develop theoretical models that can be referred to as threshold models (Copeland and Taylor, 2003). An example is Stokey (1998) who develops a model based on the interaction between the production process and consumer preferences. Stokey develops a static model of environmental regulation in which production decisions are made between a mix of conventional inputs, that generates different levels of pollution, depending on the combination of inputs. The more productive the mix of inputs, the more pollution is generated as a byproduct of the production process. Utility is negatively affected by higher amounts of pollution, creating a trade-off between consumption and pollution. The model describes a situation in which producers use the dirtiest input mix when productive capacity (income) is below a certain threshold. Above this threshold, the pollution intensity of the chosen input mix depends on consumer preferences regarding the trade-off. Below the threshold, pollution rises linearly with income, in accordance with the first half of the EKC. Above the threshold, pollution may increase if the elasticity of the marginal utility of regular consumption is higher than one. In other words, people are collectively willing to substitute away from the consumption of regular goods to achieve lower levels of pollution. Combining these trends of pollution below and above the threshold, provides a growth path of pollution that may be consistent with an EKC. Stokey organized her analysis as a social planner’s optimization problem, where one way of achieving the social optimum is through direct regulation of pollution.

The theoretical model derived by Andreoni and Levinson (2001) shows that a relatively simple setup is sufficient to find conditions under which an EKC could exist. Their model hinges on the assumption of increasing returns to scale in pollution abatement. The authors construct a one-good model, in which an individual maximizes utility, which is a function of consumption and pollution, where pollution is a function of consumption and abatement efforts. The authors derive a growth path of pollution based on the consumer’s utility maximization problem. The slope of this growth path depends on the returns to scale of pollution abatement. If returns to scale of pollution abatement are decreasing, the relationship between pollution and income will be convex (U-shape). When the return to pollution abatement is constant, the slope of the EKC will be constant and pollution will increase proportionally to income. When the returns to scale of pollution abatement are increasing, a concave pollution growth path emerges, consistent with an EKC. The authors then expand their model to include more than one individual, after which their results still hold. The authors conclude that their simple model is sufficient to derive the possibility of an EKC, by showing that their model indicates that the EKC may be the direct result of increasing returns to scale of pollution abatement.

The final theoretical model that will be reviewed is the model constructed by Jaeger et al. (2011). The authors posit that the assumptions for homothetic preferences, income thresholds and increasing returns to abatement made in some of the theoretical literature are unnecessary and that their theoretical model describes a possible growth path consistent with the EKC, without making these assumptions. They conclude that whenever production elasticity is elastic and exceeds consumption elasticity, the optimal level of environmental quality will eventually rise above the initial level of environmental quality. The authors find that if the elasticity of substitution in the production function is elastic and exceeds the elasticity of substitution in the utility function, an increase in income will eventually decrease consumption elasticity below production elasticity, resulting in higher levels of environmental quality. This result describes an optimal growth path of environmental quality that may be consistent with an EKC. The model the authors introduced can be constructed to isolate the interaction between environmental quality and income per capita and the interaction between environmental quality and population size/density. The results of the second analysis show that, under the same conditions, the optimal growth path of environmental quality, following an increasing population size, may be consistent with an EKC as well. The authors note that environmental resources that are considered essential environmental goods will have a relatively low elasticity of substitution in the utility function and are therefore more likely to exhibit an growth path consistent with an EKC.

### 2.2 Empirical Literature Review

The first study to analyze the effects of income growth on environmental quality was conducted by Grossman and Krueger (1991). In their study the authors looked at the relationship between income and air quality in 42 countries and the implications of trade liberalizations, through the North American Free Trade Agreement (NAFTA), on the environment. Grossman and Krueger investigate whether an EKC exists for sulfur dioxide ($SO_2$), dark matter (smoke) and suspended particulate matter. They estimate an EKC function that includes a squared and cubic Gross Domestic Product (GDP) per capita variable and a set of dummies for location and time. The cubed income term is added to allow for more flexibility in fitting the data. The authors find an inverted U-shaped curve with a turning point between \$4,000 and \$5,000 of Purchasing Power Parity (PPP) per capita GDP for $SO_2$ and dark matter. However, $SO_2$ emissions start to increase again after \$14,000 and dark matter increases after \$10,000, possibly suggesting that the curve is more N-shaped then U-shaped. These results could reflect that the cubed income term is capturing a leveling off effect, where emissions decrease after the second turning point at a diminishing rate. The only countries in their sample with income levels higher than \$16,000 were the United States and Canada, leading the authors to conclude that the upward trend of pollution at high income levels should not be viewed as strong evidence for an N-shaped curve. Additionally the authors find that suspended particles have a reversed N-shaped curve with turning points at $7,000 and $15,000. In 1995, Grossman and Krueger extended their previous work with additional data for other pollutants. They found similar results that showed that income was a highly significant factor contributing to changes in environmental quality and that increasing income did not unambiguously result in environmental degradation.

Empirical evidence of an EKC in the literature is mixed. Although some of the literature finds an inverted U-shaped relationship between income levels and certain environmental quality measures, the EKC does not appear for all measures of environmental quality (Stern, 2003). Examples of environmental quality indicators that have exhibited trends consistent with the EKC include dark matter (Grossman and Krueger, 1991; Shafik and Bandyopadhyay, 1992), $SO_2$ (Grossman and Krueger, 1991; Shafik and Bandyopadhyay, 1992; Selden and Song, 1993; Jaeger et al., 2011), oxides of nitrogen (Selden and Song, 1993) and $CO_2$ (Selden and Song, 1993; Day and Grafton, 2003). Findings of other studies conclude that there is no direct evidence for a relationship between income and factors of environmental quality, such as biodiversity (Mills and Waite, 2009), deforestation (Shafik and Bandyopadhyay, 1993), carbon monoxide emissions (Day and Grafton, 2003), $SO_2$ emissions (Day and Grafton, 2003) and suspended particulate matter (Day and Grafton, 2003). Arrow et al. (1995) argue that because evidence of an EKC is mixed, supporting evidence of an EKC for a specific measure of environmental quality is not sufficient to conclude that an EKC exists for environmental quality in general.

Skeptics of the EKC, find fault with some of the empirical analyses carried out in some of the EKC literature. One issue concerning empirical estimations, that has also been raised in the theoretical literature, is that the empirical literature often fails to test for endogeneity caused by the simultaneity between income and environmental quality. However, testing for endogeneity requires the use of one or several instrumental variables that could substitute for an income variable, which is not an easy task. An instrumental variable would have to be highly correlated with the income variable and would need to capture as much of income’s variation as possible, but it should not be correlated with the error term. If not enough of the income variable’s variation is captured, the interpretation of the coefficients, which is an important aspect of any EKC analysis, becomes troublesome. The instrumental variable might, for example, only be capturing the variation of the income variable for a sub-set of the countries in the sample (Kennedy, 2008). This means that the coefficient only applies to the sub-set countries and is not representative for the entire sample, or the population. If no instrumental variables can be found to account for the possible endogeneity in an EKC model, the researcher should err on the side of caution when interpreting their results, because the presence of endogeneity could lead to spurious results (Stern, 2003).

An example of a researcher who appears skeptical of the EKC is Stern (2003; 2004; Stern et al., 1996). Stern's skepticism is mostly directed towards the empirical literature, which he refers to as "econometrically weak" (Stern, 2003). Some of the problems he addresses are issues concerning heteroskedasticity and omitted variable bias. Heteroskedasticity is a violation of the homoskedasticity assumption that the disturbance terms all have the same variances and are uncorrelated with each other (Kennedy, 2008). This means that there might be sub-sets of countries that have different residuals, which could lead to an overestimation of the significance of coefficients. Omitted variable bias is a bias caused by the exclusion of relevant variables from the list of explanatory variables. Since relevant variables are often correlated with other explanatory variables, this can cause the error term to be correlated with the explanatory variables that are included in the model (Kennedy, 2008), leading to biased estimates.

An issue that is closely linked to omitted variable bias is the fact that most of the empirical literature provides little insights into the underlying mechanisms that generates an EKC. These studies often describe the statistical relationship between income per capita and environmental degradation, but they are not able to explain why a U-shaped path might occur. This lack of insight into the underlying mechanism that generates an EKC is potentially caused by the use of so called 'reduced form' equations when estimating an EKC model. The reasoning behind using a reduced form equation is that the researcher is interested in finding the total influence of income on environmental quality. Since this is the main relationship of interest, other factors that might influence environmental quality are not part of the research question and are omitted. The disadvantage is that, by doing so, any theoretical conjectures cannot directly be supported by the empirical results. In an attempt to identify some of these factors and to improve the overall fit of empirical models, researchers have added numerous additional explanatory variables, like population density, trade indicators and indicators of political and civil rights (de Bruyn, 2000).

A common issue that arises in serial panel data is serial correlation, or autocorrelation. Autocorrelation is a violation of one of the OLS assumptions (adjusted for time series). This assumption states that the errors in two different time periods are uncorrelated. The error term at time t should not be correlated with the error at time t+1 (Wooldridge, 2009). If autocorrelation is present, this assumption is violated, causing the estimated standard errors to be biased and estimation to be less efficient (Drukker, 2003). If autocorrelation is present and not accounted for, the significance of the explanatory variables could be under- or overestimated. Since most EKC studies involve time series (panel) data, tests for autocorrelation should be performed before any inferences can be drawn from the results.

**2.3 Empirical Literature using Forest Coverage**

Although the literature on an EKC between forest coverage and income per capita is less extensive than the literature that looks at indicators of air quality, Choumert, Motel and Dakpo (2012) were able to perform a meta-analysis using 71 studies, offering 631 estimations with some form of deforestation as dependent variable. The analysis carried out doesn't attempt to provide any explanations or estimations to prove the existence of the EKC for deforestation, but the paper yields some interesting results that show how the likeliness of finding evidence for an EKC depends on the researcher's strategies. The authors find that as the year of publication becomes more recent, the likeliness of finding support for an EKC for deforestation decreases, possibly due to improved econometric techniques. This is in line with what Stern (2004) indicates in his critical review of the EKC. However, the authors also find that increasing the sample size, which is more likely in recent studies, increases the chances of finding an EKC. Since a larger sample size yields stronger results, this finding seems to provide some support for the existence of an EKC for deforestation. Interestingly, the authors also find that if the author is a Masters student, the probability of finding an EKC declines. Overall the proportion of studies that find an EKC for deforestation are less than half.

An example of a study using deforestation as dependent variable was conducted by Cropper and Griffith (1994) in which they analyze deforestation rates in developing countries using an EKC framework. While their sample exists of only non-OECD countries, their analysis offers some important insights that are very relevant to this thesis, because their model uses deforestation rates as a dependent variable. Independent variables include several income variables, log prices, two population variables (population growth and rural population density) and a time trend variable. The authors find that their results are significant in two out of the three regions studied (Africa and Latin America). The income turning points they find range between $4,500 and $5,500. Since most of their observations fall to the left of these turning points, they are not able to conclude that there is an actual inverted U-shaped relationship. They find evidence that as income increases, deforestation rates level off. These results offer some support for an EKC for deforestation, but they are not conclusive. The authors also state that policymakers should not take away from their results that income growth is the solution to decreasing deforestation, as deforestation rates are still positive even beyond the income turning point.

Patel, Pinckney and Jaeger (1995) investigate whether there is an EKC relationship between forest coverage (intended for the production of fuel wood) and income in East Africa. Much like the relationship investigated in this thesis, this type of relationship would manifest itself as a U-shaped relationship as opposed to the typical inverted U-shape. Their study first involved assessing the profitability of fuel wood for smallholders in East Africa and the constraints on production faced by these smallholders. They find that tree growing is positively related with income and farm area. After testing household behavior they find that people with higher incomes tend to grow more trees, as opposed to other crops. Furthermore they find that the elasticity of farm area (on growing trees) is less than one, which implies that the number of trees on land increases as there is subdivision of land, which was a common occurrence at the time. Their results describe a U-shaped relationship between income and forest cover, where forest cover first decreases because of a rising population density and rising demand for fuel wood, and then starts to increase as land is being subdivided and more trees are being planted, as income continues to grow.

A study conducted by Galinato and Galinato (2010) uses deforestation-induced $CO_2$ emissions as a dependent variable. While the authors don't look at forest coverage or deforestation directly, this study offers some insights into the driving factors of deforestation which could be beneficial to the empirical analysis of this thesis. In this paper, the authors run a conventional EKC regression with emissions as a dependent variable and a linear and squared income variable as independent variables, but they add an explanatory variable for political stability and corruption control. The authors indicate that low political stability often hinders sustainable growth. As a result, resources aren't as well protected, which in this case would translate to higher deforestation rates. The authors also indicate that this might lead to the use of more harmful deforestation processes that lead to relatively higher $CO_2$ emissions, like the process of burning forests to clear land for agriculture. The results of this paper indicate that income per capita has a negative and significant effect on forest cover in the short run, but that there are no lingering long run effects. The results also show that politically stable countries have higher forest coverage, but countries with better corruption control have less forest coverage. The results seems to suggest that the influence of political stability is ambiguous. The authors note that they indeed observe an inverted U-shaped relationship and that the political stability variables only affect the intercept of the curve, not the slope and turning points of the curve.

## 2.4 Value of Forests and Causes of Deforestation

This section will briefly discuss how forests change; why they are valuable; and possible causes of the large deforestation rates reported by the FAO. Achard et al. (2009) report on the value of forests and the factors that damage the state of the world's forests for the United Nations Environment Program (UNEP), the FAO and the United Nations Forum on Forests (UNFF) and state the following about the changes that forests undergo:

> Forests can undergo changes in various ways. Forest areas can be reduced either by deforestation or by natural disasters such as volcanic eruptions or severe mudslides, which can result in the forest being unable to naturally regenerate. Conversely, forest area can be increased – through afforestation or by the natural expansion of forests. (Achard et al., 2009)

While natural disasters can have immediate and long lasting consequences on the survival of forests, in the last few decades deforestation has become the main destructive force to the world's forests. Deforestation is defined as a reduction, caused by human interference, of the tree cover of a forest below the threshold level that is specified in the FAO's definition of a forest. Deforestation is a historic phenomenon, more typical in the temperate regions of the world, such as Europe. However, over the last century, the majority of countries with the highest deforestation rates has shifted to the tropical regions of the world. Forest area can also decrease through forest fragmentation, which splits up a larger forest area into several smaller areas through conversion (Achard et al., 2009).

While the total area of forests in the world is declining in size, new forests have been established and already existing forests have started to expand. An expansion of forests, that is caused by human involvement, can be described as afforestation or reforestation. While these terms are sometimes used interchangeably, they are different in meaning. Afforestation is the planting of trees in areas that was previously not forest land, while reforestation is the planting of trees in an area that was previously deforested or in an area of which trees were destroyed by natural causes. Under the right climatic conditions, forest also have the ability to expand through natural (re)generation. Forests expand faster in humid climates with plenty of rain. The sum of all positive and negative changes to forest areas, through natural causes or human involvement, is the net change in forest area. The global net change in forest area has been negative for decades and the consequences have been detrimental to environmental, economic and social services, (Achard et al., 2009).

Forests are valuable resources that serve many purposes. One of these purposes is the production of wood products, which covers a wide variety of items that use inputs from forests such as: timber, fuel wood, charcoal, raw material for panel production and pulpwood (Achard et al., 2009). When demand for wood products increases, the demand for their inputs will increase as well, which leads to increased pressure on forests. Forests also provide other essential services to the benefit of people. These services and their values are often different in developed and developing countries. Dependence on forests for a livelihood is common, particularly in developing countries, where people depend on forests for: shelter; the provision of fuel wood; the provision of wildlife, plants and herbs; and medicinal needs (Achard et al., 2009). In developed countries people are less likely to depend solely on forests for their livelihoods, but forests still provide essential services such as recreation. It is apparent that the desire to harvest wood to be used as an economic input and the desire to conserve forests are in competition with each other, and both come at a (social) cost. An example of the cost of conservation is the loss of economic activities, such as the timber industry or the clearance of forested land for development purposes, such as agriculture or infrastructure. Examples of the cost of deforestation are damages to ecosystems and the disturbance of economic and social services that forests provide. The costs of deforestation are described in more detail below.

The effects of deforestation can be catastrophic to the ecological services that forests provide. Forest interacts closely with water cycles. Trees act as water pumps, provide water storage, percolate water into soil and through evapo-transpiration, pump water into the atmosphere. Harvesting trees breaks the link between the water cycle and ecosystems and can have dire consequences for their survival. In tropical rainforests, such as the Amazon, scenarios have been projected that predict decreases in local precipitation and evapo-transpiration to the extent that large areas of land are at risk of sustained desertification. The consequences of this scenario are devastating to local ecosystems and even the global climate. Forests also provide habitats for about 80 percent of the world’s terrestrial animals and are therefore one of the biologically richest ecosystems in the world. Deforestation of forests destroys these habitats and seriously endangers a myriad of terrestrial animals, causing widespread biodiversity losses (Achard et al., 2009).

Another example of ecosystem services provided by forests includes the ability to absorb carbon dioxide from the air and store it as biomass, serving as natural carbon storage tanks. In doing so, forests play a vital role in the reduction of carbon in the atmosphere. Deforestation not only causes less carbon to be absorbed from the atmosphere, but also causes the carbon that is stored as biomass to be released into the atmosphere. Forests are therefore a vitally important link in the carbon cycle and consequently deforestation is considered one of the main drivers of climate change (Achard et al., 2009). While biodiversity losses and soil degradation are often irreversible, the release of carbon into the atmosphere can potentially be reversed, through carbon sequestration. Planting trees is a type of carbon sequestration that allows for the semi-permanent storage of carbon as biomass (Zomer et al., 2008). (Re)planting trees can therefore help absorb some of the excess carbon in the atmosphere. The planting of trees, however, does not necessarily restore biodiversity nor does it reverse soil degradation because these damages are often irreversible (Wenhua, 2004).

As mentioned, deforestation not only affects ecosystems, but can also adversely affect vital economic and social services. Forests contribute to the provision of clean water, through the prevention of soil erosion and floods and natural filtration processes. Deforestation removes this natural barrier that prevents the contamination of ground water and surface level water sources and poses significant health concerns. Many people, worldwide, rely on water that comes from watersheds that contain clean water due to the presence of forests. Floods caused by soil erosion are not only a threat to drinking water, but can also be dangerous to human beings and animals alike. Forests can also considerably reduce the monetary and physical damages caused by flooding (Achard et al., 2009).

Since forests are such a valuable resource it is important to find the right balance between the rate at which trees are harvested and the conservation of forests. This issue has been debated for many years and there is no single answer to the question: What is the optimal (global) deforestation rate? One question that has arisen in this debate is what the relationship is between changing forest levels and income or population pressures. The analysis conducted for this paper will not attempt to find the exact rate of deforestation that is optimal for society, but seeks to shed some light on the interaction between income, or population density, and changes in forest levels over time. In order to do this, it is important to understand and control for the factors that affect changes in forest levels to isolate the effect of income and population density. The causes of deforestation identified in this section were therefore used to construct the set of additional explanatory variables that will be discussed in the empirical approach of this paper.

Cropper and Griffith (1994) identify 3 main causes of deforestation. These are: the conversion of forest land to arable land for crops or pastures, harvesting of logs and harvesting of firewood. The root cause of all three is usually identified as population pressure, although income levels have also been linked to these causes, especially through the demand for harvested wood. The underlying causes of deforestation listed by the Achard et al. (2009) are population pressures that affect the demand for land, poverty, lack of enforceable property rights and lack of incentives to establish adequate forest management services.

Controlling for these causes is an important aspect of an analysis that looks at the development of forest coverage over time.

**3. Theoretical Foundation**

This section will lay out the basic theoretical foundation of the relationship between environmental quality, measured by the stock of forests, and income per capita. We assume an economy with a fixed number of n identical individuals whose preferences over the consumption of goods (C), and the amenities that a stock of forests provide (A), are described by a strictly concave utility function. An example of an amenity of the stock of forests is a richer, more aesthetic and clean environment, because of increased biodiversity. There are two inputs for consumption, $X_1$ and $X_2$, where input $X_1$ negatively affects the stock of forests, input $X_2$ has no negative effect on the stock of forests and is equally productive as $X_1$ but more costly to implement. Examples of $X_1$ are the use of wood as an input to production or the clearing of forested land for agriculture. Assume that the stock of forests is only affected by the consumption of $X_1$ and that when the use of $X_1$ falls below a certain value, forests will start to regenerate. The utility function, budget constraint and production function are presented below.

$$U = U(C, A) \tag{1}$$

$$Y = X_1 + \theta X_2 \tag{2}$$

$$C = C(X_1, X_2) \tag{3}$$

The budget constraint illustrates that the consumer can spend her total income (Y) on input $X_1$ or input $X_2$, where the cost of $X_1$ is normalized to 1, and $\theta > 1$, because $X_2$ is more costly to implement. This implies that given a level of Y, fewer $X_2$ inputs can be utilized compared to $X_1$ and a combination of inputs that uses $X_2$ abundantly is less productive than a combination of inputs that predominantly uses $X_1$. The partial derivatives of the utility function are $\frac{\partial U}{\partial X} > 0$ and $\frac{\partial U}{\partial A} > 0$; the second order partial derivatives are $\frac{\partial^2 U}{\partial X^2} < 0$ and $\frac{\partial^2 U}{\partial A^2} < 0$, indicating that both increased consumption and amenities of a larger stock of forests increase utility at a decreasing rate. For the amenities of the stock of forests this implies that the larger the stock, the less additional utility is derived from its amenities.

We can present A as a function of the stock of forests (S), which is a function of $X_1$.

$$A[S(X_1)] = F - z(nX_1) \qquad for\ X_1 > \varphi$$

Where the stock of forests is equal to an initial endowment of forests (F) minus the amount of deforestation (z) as a function of $X_1$ and the population size (n). $\varphi$ is the critical value of $X_1$ below which forests are able to regenerate toward the initial stock of forests. The derivative $\frac{\partial A}{\partial S} > 0$ implies that as the stock of forests grows, the level of amenities increases.

Society's maximization problem is therefore

$$\begin{aligned} \text{max:}\quad & n \cdot U(C, A) \\ s.t.\quad & C = C(X_1, X_2) \\ & Y = X_1 + \theta X_2 \\ & A = A[F - z(nX_1)] \end{aligned}$$

Rewriting the constraints and plugging them into utility leads to the unconstrained maximization problem for $X_1$ below:

$$\text{max:}\ \ n \cdot U\left[C\left(X_1, \frac{Y - X_1}{\theta}\right), A[F - z(nX_1)]\right]$$

The first order conditions of this maximization problem will result in the optimum level of consumption and stock of forests, given a certain level of income. Using these optimum levels, we can trace the socially optimum growth path of the stock of forests as income increases. The analysis that follows will describe what this growth path may look like under different conditions.

Using the general theoretical set-up above, and the theoretical model described by Stokey (1998), we can examine how the growth path of the stock of forests can be affected under different conditions. Stokey identifies 2 different types of technologies: dirty technologies that have detrimental effects on environmental quality, in this case measured by the stock of forests, and clean technologies, that are less productive, but don't affect the stock of forests. This idea resonates with the set-up described above, where production can be described as a function of a dirty ($X_1$) and a clean input ($X_2$). A technology that uses a combination of inputs that relies more heavily on the dirty input is therefore a dirty technology. A clean technology uses a combination of inputs with an abundance of the clean input and is less detrimental to the stock of forests, but less productive than the dirty technology.

It can be shown that there is an income threshold, below which the marginal utility gained through increased production, exceeds the marginal disutility associated with the increased use of $X_1$. As income increases towards this threshold, it is socially optimal for consumption to increase exclusively through the use of the dirty technology. At income levels above this threshold, due to the concavity of utility, the marginal disutility of the use of $X_1$ will outweigh the marginal utility gained through increased consumption and it will be socially optimal for production to shift towards the use of cleaner technologies. This will alleviate the strain on the stock of forests because input $X_2$ is used progressively more than input $X_1$. While the model suggests that this should occur because it is the social optimum, this path can also be achieved through a government standard on the use of $X_1$. Alternatively, the government could set a Pigouvian tax on $X_1$ to maximize the utility of consumers, which would limit the use of $X_1$, it can be shown that at income levels below the threshold it is optimal for the standard to be lax or the tax to be relatively low. However, as income increases above the threshold, the standard becomes stricter and tax increases, following the social optimum, forcing production to use the less productive input $X_2$ progressively more. Whether the government intervenes, or not, the model provides a scenario in which the optimal growth path of the stock of forests will decrease, but will eventually level out as the use of $X_1$ decreases. Once the use of $X_1$ decreases below the critical value ($\varphi$), the natural growth rate of forests will increase the stock of forests, creating the possibility of a growth path consistent with the EKC.

Using the same set-up as before, and the theoretical model described by Jaeger et al. (2011), we can examine how a new set of conditions affect the growth path of the stock of forests. Assuming constant elasticity of substitution in both the utility and production functions, it can be shown that "a parametric change will increase optimal environmental quality if and only if the change increases production elasticity relative to consumption elasticity at the initially optimal environmental quality level" (6). In the set-up above, this means that after a parametric change the optimum stock of forests will increase if:

$$\varepsilon_C \geq \varepsilon_U$$

$$\left|\frac{dA/dC}{A/C}\right|_C \geq \left|\frac{dA/dC}{A/C}\right|_U$$

Where the authors define production elasticity ($\varepsilon_C$) and consumption elasticity ($\varepsilon_U$), at any point on the production possibilities frontier of (C, A), as the slope of the frontier divided by $A/C$. This is equivalent to the percentage change of C, divided by the percentage change of A. It can be shown that, as income increases, the consumption elasticity converges to zero, if the elasticity of substitution between consumption and the stock of forests in the production function is elastic and exceeds the elasticity of substitution between consumption and the stock of forests in the utility function. This implies that the optimum stock of forests will eventually increase as income increases. If we assume that forests are considered an essential environmental good, the elasticity of substitution in the utility function is expected to be low, increasing the chance that the optimum growth path of the stock of forests is consistent with an EKC.

Following the same theoretical framework by Jaeger et al., we now let $n$ vary in size, holding $Y$ fixed. This will allow us to describe a potential growth path of the stock of forests as the population size, or density, increases. The key aspect of this approach is examining how changes in $n$ affect production and consumption elasticity. If an increase in $n$ reduces consumption elasticity compared to production elasticity, we may see an increase in the optimal stock of forests. It can be shown that, as $n$ increases, the consumption elasticity converges to zero if the elasticity of substitution in the production function is elastic and exceeds the elasticity of substitution in the utility function. This result is analogous to the result that was derived when $Y$ was allow to vary and $n$ was fixed. The optimum growth path of the stock of forests, following increasing population density, may therefore be consistent with an EKC as well.

The theoretical analysis conducted in this section has described a number of ways in which the optimum growth path of environmental quality may be consistent with an EKC. Following Stokey's framework, the growth path of the stock of forests may be consistent with an EKC if a type of clean technology is present that kicks in when income reaches a certain threshold. This technology is less productive than a dirty technology, but at income levels that are sufficiently high the utility derived from a larger stock of forests outweighs the utility derived from additional consumption, and the clean technology is preferred over the dirty technology. A simple example of a clean technology relating to forests would be switching to building brick houses, from building wooden houses, relaxing the strain put of the stock of forests. Jaeger et al. show that a growth path consistent with an EKC may occur if the elasticity of substitution in production is elastic and exceeds the elasticity of substitution in utility. This framework allows for the possibility of an EKC with respect to population density as well. The expected relationship between the stock of forests and income per capita in this case is a U-shaped curve where the stock of forests initially decreases when income or population density increases, but reaches a turning point after which the stock of forests will increase again.

## 4. Methodology

### 4.1 Empirical Approach

The theoretical underpinnings described the previous chapter indicate the possibility of an optimal growth path for environmental quality that is consistent with an EKC. The theory behind the EKC indicates that the growth path of forest cover may have a causal relationship with income per capita and population density. In an attempt to test whether the growth path of forest coverage follows an optimal growth path that is consistent with an EKC, the following equation is estimated to test the relationship between the stock of forests and both income per capita and population density:

$$F_{i,t} = \alpha_i + \beta_1 \cdot Y_{i,t} + \beta_2 \cdot Y^2{}_{i,t} + \beta_3 \cdot Y^3{}_{i,t}$$
$$+\beta_4 \cdot D_{i,t} + \beta_5 \cdot D^2{}_{i,t} + \beta_6 \cdot D^3{}_{i,t} + \varepsilon_{i,t}$$

In this panel estimation the subscript $i$ represents country $i$ and $t$ represents year $t$. $F$ represents the stock of forest, which is measured as the share of land in forests. $Y$ is per capita GDP in International Dollars (2005 base year) and $D$ is population density, expressed as the number of people per square kilometer. The latter two variables enter as third order polynomials to allow for a nonlinear relationship and the possibility of a U-shaped path. Stokey (1998) notes that in her model a cubic approximation of income may perform significantly better at fitting the upper tail of the EKC. The cubed income and density terms are therefore added to the equation to investigate whether this functional form fits the data better. A significant (negative) cubed income or density term, doesn't necessarily imply that the share of forests starts to decrease after the second turning point of the curve. It may be an indication of a leveling off effect, where the share of forests increases at an ever-slowing rate after the first turning point. This equation will be referred to as the reduced form equation because it is estimating the total effects of income per capita and population density on the share of forests.

To the extent possible, we wish to include other explanatory variables that affect forest cover to avoid misspecification bias. When these variables are excluded from an estimation, their effect on forest cover will be captured by the error term. If these variables are correlated with income per capita and/or population density and are not explicitly included in the estimation, the error term may be correlated with the explanatory variables, which is a violation of the zero conditional mean assumption (Wooldridge, 2009). A violation of this endogeneity assumption, may cause biased estimators of those explanatory variables that are correlated with the error term. The coefficients of income per capita and population density, may therefore be under- or overestimating the effect that income per capita and population density have on the share of forests.

Based on the literature review, a number of factors are believed to influence forest cover or the level of deforestation. Precipitation and temperature are important factors that influence the stock of forests. Tropical climates with plenty of precipitation tend to be very suitable for the growth of forests, while arid countries, with little to no precipitation, are less suited for forest growth (Achard et al., 2009). Climate is therefore an important variable to consider and is included in the estimation. The climate variables are a set of 5 dummies that indicate whether a country's dominant climate type is hyper arid, arid, semi-arid, dry sub-humid or humid. The first 4 climate types will be compared to humid climates. Since the climate dummies will only affect the intercept the 4 dummies that are included are all expected to be negative because more humid countries are more suitable for forest growth.

Other explanatory variables of interest are variables that may indicate why a country will stray from the optimum growth path predicted by theory. Weak political institutions might, for example, lead to a situation in which a country might not follow the optimum growth path of forest cover. In the literature, a lack of enforceable property rights has been recognized as a potential cause for poor protection of resources, leading to relatively higher extraction of those resources (Nguyen and Azomahou, 2007; Galinato and Galinato, 2010). A variable that could capture a lack of protection or enforceable property rights is a measure of political rights and civil liberties. Countries that score well in these categories tend to have properly defined institutions and provide adequate protection of their resources. Proper protection of forests, especially the protection of publicly owned forests which take up over 80% of the World's forests (Achard et al., 2009), therefore results in relatively lower deforestation rates. This variable will be included as dummy variable, equal to 1 for countries designated as "free" and "partly free", based on their relative scores for political rights and civil liberties. These countries will be compared to countries that are designated as "not free". Partly free and free countries are expected to have better protection of forests than the countries that are not free. The expected signs of these dummies are therefore positive, where free is larger in magnitude than partly free. How these dummies were created will be described in section 3.3.

Another indicator of why a country strays from the optimum growth path of the share of forests is that information about the value of forests is incomplete or inaccurate. Theory suggests that at high income levels, consumers are willing to substitute additional income (to be spent on regular consumption) for increased environmental quality. While deforestation and the state of the world's forests have been a widely debated cause of concern in the media, scientific literature and educational settings, awareness of the importance of conserving natural forests, especially tropical forests, is an important aspect of whether additional income will be spent on the conservation of forests. Organizations like UNEP, FAO and UNFF try to communicate the value of forests to both policy-makers and the wider public, by publishing reports, such as Vital Forest Graphics (Achard, 2009), that summarize and explain the value of forests and the issues that many (tropical) forests face. A variable that will capture how aware consumers are of the importance of forests is the quality of education that is available to these consumers. An individual that is highly educated would, for example, likely be more aware of these issues and may be more likely to spend their income on conserving forests or spreading awareness by, for example, lobbying policy-makers. Education might therefore be an important indicator for slowing deforestation rates and possibly even increasing reforestation or afforestation rates. Education will be included as an explanatory variable, measuring the percentage of the population that is at least 15 years old and does not have any education. The coefficient associated with this variable is expected to be negative: if the percentage of people with no education increases, forest areas are expected to decline faster. One issue that might arise is that education is highly correlated with income and the inclusion of both variables in the same estimation might weaken the significance of one or both variables.

Jaeger et al. (2011) describe a situation in which the willingness to substitute consumption for increased environmental quality may be affected by the extent of income inequality. This phenomenon can be explained through the income threshold framework developed by Stokey (1998). This framework predicts that as income per capita increases, individuals with income above the threshold will shift their resources towards a clean input or production technology, while those who are still below the threshold still spend their resources on the dirty technology. Jaeger et al. note that high income inequality may be beneficial to environmental quality at low per capita income levels, because the richest segment of the population will reach the threshold faster and will start spending resources on clean technologies. However, high income inequality becomes detrimental at high per capita income levels because there are still segments of the population that have income levels below the threshold. Countries with higher income inequality may therefore have different growth paths and may still see decreasing environmental quality where countries with the same average income levels, but less inequality, do not. Income inequality, measured by a Gini coefficient, may therefore capture the fact the countries with more income inequality have different slopes than countries that are more equal. The Gini coefficient is a continuous number between 0 and 1, where higher numbers represent more income inequality. The variable will be introduced to the model as a linear interaction term with all the per capita income variables, because it is expected to change the slope between income per capita and the share of forests. The expected signs and magnitudes of the interaction terms are hard to predict because they depend on the magnitude of the Gini coefficient and because income per capita enters the estimation equation as a third order polynomial. However, the presence of income inequality is expected to increase the variability of an observed EKC. The signs of the coefficients are therefore expected to be the same as the signs of the income variables, indicating that the slope of an EKC become larger in magnitude as income inequality increases. The signs are therefore expected to be negative, positive and negative for the linear, squared and cubed interaction terms respectively.

The complete model that is estimated is therefore:

$$F_{i,t} = \alpha_i + \beta_1 \cdot Y_{i,t} + \beta_2 \cdot Y^2{}_{i,t} + \beta_3 \cdot Y^3{}_{i,t}$$
$$+\beta_4 \cdot D_{i,t} + \beta_5 \cdot D^2{}_{i,t} + \beta_6 \cdot D^3{}_{i,t} + X_{i,t} + Z_i + \varepsilon_{i,t}$$

which is the reduced form equation, with the addition of the vectors of explanatory variables, $X$ and $Z$. All time varying explanatory variables (political freedom, education, income inequality) are included in vector $X$ and the time unvarying explanatory variables (climate) are included in $Z$.

**4.2 Data Description**

This section describes the data used in the estimation of the model. First, the data for the dependent variable, the share of land in forests, will be described, followed by a description of the data for the explanatory variables.

The dependent variable that is used as the measure for environmental quality is the share of the total land area, of each country in the sample, that is covered by “forests”. The data on forest coverage was retrieved from the Global Forest Resource Assessments (FRA) conducted by the Food and Agriculture Organization of the United Nations (FAO). The FRAs report total forest area and other wooded land areas in thousands of hectares, for a set of countries in 4 continents, Africa; America; Asia and Europe. The definition of forest as used in the latest FRA (2010) is: “Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use”. The data on “other wooded land areas” was excluded from the sample because of missing data and changing definitions between 1950 and 2010.

In total there are 11 FRA reports starting in 1948, when the first FRA was conducted. Between 1948-1963 the FRA was conducted every 5 years. Between 1963-1989 the FRA was conducted less frequently and some reports did not cover all continents or only covered tropical forest areas. In this time period there was an unofficial FRA in 1974 (Person, 1974) and an interim report in 1988. The report by Person, who was employed by the FAO and worked on earlier versions of the FRAs, was completed under agreement and cooperation by the FAO and the Royal College of Forestry in Stockholm. The FAO did not issue a report at the time because of insufficient funds and provides a link to the report on their website as an alternative resource that uses the same methodology and roughly similar definitions that were used in earlier FRAs. After 1988 FRAs were conducted every 5 years starting in 1990. The FAO database seems to be the only database that covers areas of forest coverage dating this far back. However, the data is known for being inconsistent. The definition of forest used in some the reports differs from other reports. For this reason the FRA from 1948 was excluded from the sample and the rest of the data required close examination to identify outliers. Report 10 from 2005, reported data on forest coverage for the years 1990, 2000 and 2005. Under the assumption that the most recent reports are the most accurate, reports 7 and 9 (covering 1990 and 2000, respectively) were also not used.

The reports provide data on forest coverage for the years that precede the official release data of the report. Below is a table that provides some insights in the year of issue and the years that are covered by the data in these reports. Only the reports that were used are listed in the table. As is clear from the table below, the number of years between reports is not always equal. Weighted averages between some of the reports were taken to create intervals of roughly 5 years. The panel's time variable, referred to as t, will therefore be $t = 1, 2, 3, \dots, 13$, where $t = 1$, refers to the data from 1950 and $t = 13$, will refer to data from 2010, with 5-year intervals.

**Table 1: Global Forest Resource Assessments**

| FRA Report (Year Issued) | Data Coverage[1] |
|---|---|
| **1953** | 1950/1951 |
| **1958** | 1955/1956 |
| **1963** | 1960/1961 |
| **1974** | 1970/1971 |
| **1988** | 1980 |
| **1997** | 1995 |
| **2005** | 1990, 2000, 2005 |
| **2010** | 2010 |

The data on total land area was retrieved from the FAO database FAOSTAT. It includes the same countries as the forest coverage data from the FRAs and is also reported in thousands of hectares. The data was reported yearly with the earliest observations starting in 1961 and the final observations in 2011. The data was extrapolated to include observations for the missing data starting in 1950. It was assumed that the total area of land was constant in this period and equal to the earliest observation that was available for each country. Once the total land area dataset was complete, the proportion of forest coverage with respect to total land area was calculated to create a dependent variable with at most 13 observations for each country in the sample. The dependent variable will be referred to as Forest.

Data on population density was acquired from the United Nations' Population Division. The UN database provided a complete dataset with the total population and population density per country between 1950 and 2010. The data was transformed to match the dependent variable, by reducing the interval between observations to 5 years. For each year of forest coverage data, the average population density was taken of the 5 years preceding that year, excluding the year itself. For example, for the year 1995 the average was taken over the years 1990, 1991, 1992, 1993 and 1994. The first year, 1950, was the only exception to this rule because there was no data available for the 5 years prior. Therefore, instead of taking an average, the population density of 1950 was matched with all forest coverage observations from 1950.

[1] These years differ per country as the data for some countries covers a range of years, while other data is only estimated for 1 year. The years noted in this column are an estimate for the average year of estimation of all countries.

Income  per capita data was obtained from a study conducted by James, Gubbins, Murray and Gakidou (2012). This study collected 7 time series data sets from 5 different sources: the International Monetary Fund (IMF); the University of Pennsylvania Center for International Comparison of Production, Income and Prices (Penn); the World Bank; the United Nations Statistics Division (UNSD); and the Maddison Project Database. The time series are reported in either International Dollars with 2005 as a base year, International Dollars with 1990 as a base year or US dollars with 2005 as a base year.  The authors' goal was to create a comprehensive time series data set for income per capita from 1950 to 2015, for each of the 7 time series available. They imputed the missing data for each time series by estimating growth rates for each time series and using these to estimate and fill in missing data. Once the 7 series were complete they derived a new time series of income per capita that addressed the differences between the 7 original sources. An average was taken of the 3 data series that were reported in International Dollars (2005 as base year) to create the Institute for Health Metrics and Evaluation (IHME) time series, in for the same currency. The IHME time series in US dollars with 2005 as a base year was created by averaging the 3 time series that were reported in that currency. The Maddison data was excluded in this part of the process. All time series that were made available by the authors and are summarized in Table 2.

**Table 2: Income per Capita Time Series**

| Source | Currency | # of Imputed Observations | Original Time Span |
|---|---|---|---|
| **IMF** | ID (2005) | 8044 | 1980 – 2015 |
| **Penn** | ID (2005) | 5340 | 1950 – 2009 |
| **World Bank** | ID (2005) | 8964 | 1960 – 2009 |
| **IMF** | USD (2005) | 8054 | 1980 – 2015 |
| **World Bank** | USD (2005) | 6490 | 1960 – 2009 |
| **UNSD** | USD (2005) | 6080 | 1970 – 2009 |
| **Maddison** | ID (1990) | 5378 | 1950 - 2008[2] |
| **IHME** | ID (2005) | | 1950 – 2015 |
| **IHME** | USD (2005) | | 1950 – 2015 |

Source: James, S. L., Gubbins, P., Murray, C. J. L., & Gakidou, E. (2012). Developing a Comprehensive Time Series of GDP per Capita for 210 Countries from 1950 to 2015. *Population Health Metrics*, *Population Health Metrics 2012*(10:12). doi:10.1186/1478-7954-10-12

[2] This database was updated in January 2013 to include the years 2009 and 2010.   Source: http://www.ggdc.net/maddison/maddison-project/data.htm

The authors indicate that, for a set of countries, there is a lot of variation between each time series and it is difficult to identify which data is more accurate and an average of the time series mitigates some of this variation. The data that will be used for the empirical analysis of this thesis will therefore be the IHME data in International Dollars with 2005 as a base year. The reason for choosing the International Dollar as a currency over the US dollar is that the International Dollar has been adjusted for purchasing power parity. The US dollar time series was created using exchange rates, which tends to decrease per capita income of developing countries compared to developed countries (Stern, 1996). The IHME series that is adjusted for purchasing power parity more accurately reflects people's relative spending power, because it compares consumers relative spending power and ability to buy similar goods with the same budget. The data were transformed to create 5 year intervals, using the same method that was applied to population density.

The data on income inequality was obtained from the Standardized World Income Inequality Database, created by Frederick Solt. The Gini coefficients from the latest update (version 4.0) were used to serve as a measure for income inequality. Stolt (2013) states that the Gini coefficient is: "an index of inequality in equivalized household disposable income (post-tax and post-transfers)". Data from a large number of different sources was used to construct a time series for Gini coefficients between 1961 and 2012. Missing data was filled in through imputation to construct an inequality index that was comparable across all countries. The exact methods can be found in Solt (2009). The database contains a set of 100 imputed time series of which the average was taken to calculate a net Gini coefficient. 5-year averages were taken of the net Gini times series to create 5 year intervals, using the same method that was applied to population density.

The education data comes from from the World Bank's Education Statistics Portal. The data covers the percentage of people, over the age of 15, who have not completed primary school. This allows for a comparison of education levels across the countries in the sample. The data starts in 1970 and is recorded every 5 years until 2010.

Indicators of political freedom and civil liberties, also used by Van and Azomahou (2007), was obtained from an organization called the Freedom House. The data is reported yearly, starting in 1972, and gives countries a score based on their political rights and civil liberties. Each category is reported on a scale from 1 to 7, where 1 represents the highest form of freedom. The average of the two categories represents the country's freedom score. Before 2003, an average freedom score between 1 and 2.5 gave a country a "Free" rating; an average freedom score between 3 and 5.5 gave a "Partly Free" rating; and an average freedom score between 6 and 7 gave a “Not Free” rating. After 2003, the “Partly Free” category changed to a range between 3 and 5. Two dummy variables were created to represent free and partly free countries, respectively. Each country’s earliest observation was used to fill the gap between 1950 and its start date. The underlying assumption is therefore that these countries did not undergo any significant political changes in this period.

Finally, a set of climate dummies was created to differentiate between different types of climates. An aridity index was used to divide countries into 5 climate classes: hyper arid, arid, semi-arid, dry sub-humid and humid. This data was retrieved from the CGIAR-CSI Global-Aridity and Global-PET Database (Zomer et al., 2007; Zomer et al., 2008). The data consist of one aridity index for each of the 200 countries in the set, as climate generally doesn’t change over a period of 60 years. As is clear from the table below, most countries that are left in the sample are humid countries, with favorable climates for forest growth. The division of countries in the sample is very similar to the global dataset with 200 countries. The countries in the sample are therefore a good representation of the population, with respect to different types of climates.  Humid countries will serve as the baseline for these dummy variables, because they appear to be the norm.

**Table 3: Climate Classes**

| **Aridity Index Value**[a] | **Climate Class**[a] | **Countries in CGIAR Dataset** | | **Countries in Sample** | |
|---|---|---|---|---|---|
| **< 0.03** | Hyper Arid | 3 | 1.5% | 1 | 1.1% |
| **0.03 – 0.2** | Arid | 21 | 10.5% | 9 | 9.5% |
| **0.2 – 0.5** | Semi-Arid | 20 | 10% | 11 | 11.6% |
| **0.5 – 0.56** | Dry Sub-humid | 12 | 7% | 5 | 5.3% |
| **> 0.65** | Humid | 142 | 71% | 69 | 72.6% |

[a] Source: Thomas, D., & Middleton, N. (1997). *World Atlas of Desertification* (2nd ed.). London: United Nation’s Environmental Program.

**Table 4: Descriptive Statistics**

| | Variable | # of Observations | Mean | Std. Deviation | Range |
|---|---|---|---|---|---|
| Continuous Variables | Forest Share | 775 | 0.36 | 0.23 | 0 – 0.95 |
| | Y ($ ID) | 1248 | 6861.85 | 8574.43 | 154.49 – 54,563.61 |
| | Pop. Density | 1248 | 71.58 | 98.02 | 0.5 – 1016.59 people |
| | Gini | 536 | 36.52 | 10.43 | 16.82 – 68.03 |
| | No Education (Age 15+) | 720 | 23.06 | 24.59 | 0.07 %– 93.51% |
| Binary Variables | Climate Variables | 1248 | . | . | 0 – 1 |
| | Free | 1235 | 0.37 | 0.48 | 0 – 1 |
| | Partly Free | 1235 | 0.29 | 0.46 | 0 – 1 |
| | Not Free | 1235 | 0.34 | 0.47 | 0 – 1 |

### 4.3 Method of Estimation

The data that has been collected to test the hypotheses of this thesis is cross-country panel data that covers the time period between 1950 and 2010. One major advantage of panel data is that it can be used to counter unmeasured heterogeneity between countries in the sample. The countries used in this analysis all differ in fundamental and often unmeasured ways. While some country characteristics, like income or climate, are freely available and are included in the analysis, data on other differences is harder to find because these are difficult to observe. Omitting difference between countries that don't vary over time in regular OLS can cause biased estimations. The use of panel data allows for these differences to be excluded from the set of explanatory variables and corrects the estimation bias caused by them (Kennedy, 2008).

Using a fixed or random effects model when estimating an EKC removes the unmeasured heterogeneity between countries by omitting the general intercept and subtracting from each country's observation the average value of the variable to which that observation belongs. This method is equivalent to adding a set of dummy variables, that capture the fixed effect of each country, in the estimation. The fixed effects estimator eliminates the bias caused by the unmeasured heterogeneity of the countries in the sample. Two drawbacks of using a fixed effects estimator are that by implicitly adding a dummy for each country in the sample, a significant number of degrees of freedom are lost: one degree of freedom for each country minus a degree of freedom that was gained from omitting the intercept. This reduces the efficiency of the estimates. The second drawback is the fact that a fixed effects estimation doesn't allow for time-invariant variables, such as climate, to be included as explanatory variables. Since all observations belonging to those variables, will just have zero values (Kennedy, 2008).

A random effects estimation overcomes the drawbacks caused by fixed effects estimation. Random effects estimation allows for time-invariant variables to be included in the model while still implicitly incorporating different intercepts for each country. The random effects estimator views these intercepts as having been drawn randomly from a distribution and treats them as part of the error term. This may be a very strong assumption to make because some of the explanatory variables may be correlated with the intercepts of the countries in the sample. If this correlation is present, the coefficients of the explanatory variables will be correlated with the error term, causing biased estimators. If this correlation is not present random effects will correctly estimate the potential slope of an EKC and is superior to the fixed effects estimator because it is more efficient (Kennedy, 2008). The Hausman test will be performed on the estimates of the fixed effects and random effects regressions to evaluate whether the random effects assumption is violated or not. If the hypothesis is rejected at the 5% significance level there are systematic differences between fixed and random effect implying that fixed effects is superior.

### 4.4 Treatment of Outliers

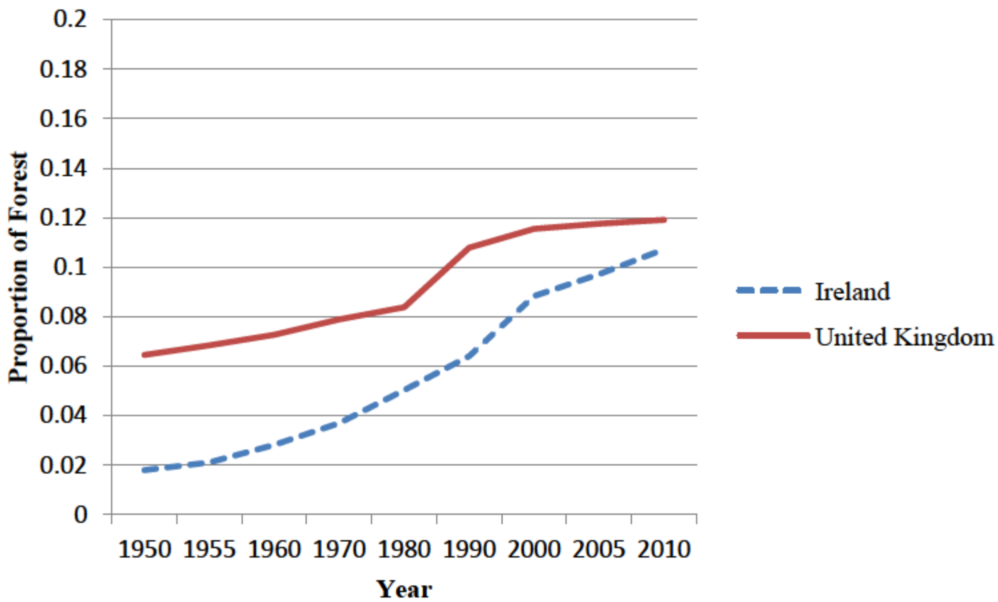
Examination of the data revealed a number of irregularities and outliers, suggesting some measurement or reporting errors. Some of these observed patterns were clearly unrealistic, in terms of changes in forested area (increasing or decreasing) over a five-year period. Given the potential effects these data problems could have on our ability to detect the true underlying relationships of interest, a set of objective screening rules were formulated to exclude specific countries that did not pass these tests. These rules are specified as follows. First, all countries that did not have at least 3 years of data were excluded from the sample. Most of the countries that were excluded in this process were colonies that became independent in the period between 1950 and 1970 and consequently stopped reporting forest areas. The remaining data was then examined to look for unusual temporal patterns in forest cover. Some countries such as the Central African Republic exhibited implausible time trends of forest areas with large increases or decreases in a matter of 5 years and were completely removed from the sample.

After the first round of eliminations a rule was set to identify single observations as outliers in the sample. These outliers were identified by evaluating their value compared to the previous and subsequent observation. An observation was considered an outlier if it had a value that exceeded a 10% increase or a 20% decrease in forest area, over an interval of 5 years, compared to the previous observation. If the observation in question occurred in 1990 and the previous observation occurred in 1980, the percentage change would be divided by 2 to calculate the 5 year change of forest area. The reason for choosing an asymmetric rule is that it is feasible to cut down larger areas of trees than it is to plant and grow new trees in a short period of time. Even though the FAO data includes newly planted forests in the definition of forest area, planting new trees requires land to be available, while clearing land of trees makes land available and is therefore relatively easier. An observation that met these criteria wasn't immediately removed as an outlier. Each observation that met the criteria for identifying an outlier was first compared to the overall time trend of the country, before being removed.

### 4.4.1 Ireland and the United Kingdom

Ireland and the United Kingdom had several outliers given the criteria above, but their overall trends seemed to suggest the observations were actually accurate. In the seminar proceedings for Afforestation in the Context of SFM, Allen et al. (2002) indicate that Ireland has one of the highest afforestation rates in the world because of its favorable climate and because the forestry sector is highly regulated by the Irish government, which encourages afforestation by providing subsidies to farmers who plant trees on their arable land. This explains the rapid afforestation that Ireland has experienced, especially after 1980. In the same proceedings, researchers note that the Scottish government (Smith, Rayner and Green, 2002), as well as the British government (Pommerening, 2002), heavily regulate the forestry sector and encourage afforestation, explaining the rapid growth of forests in the United Kingdom. The trends shown in the graph are backed up by several sources, other than the FAO database, and were not removed from the sample.

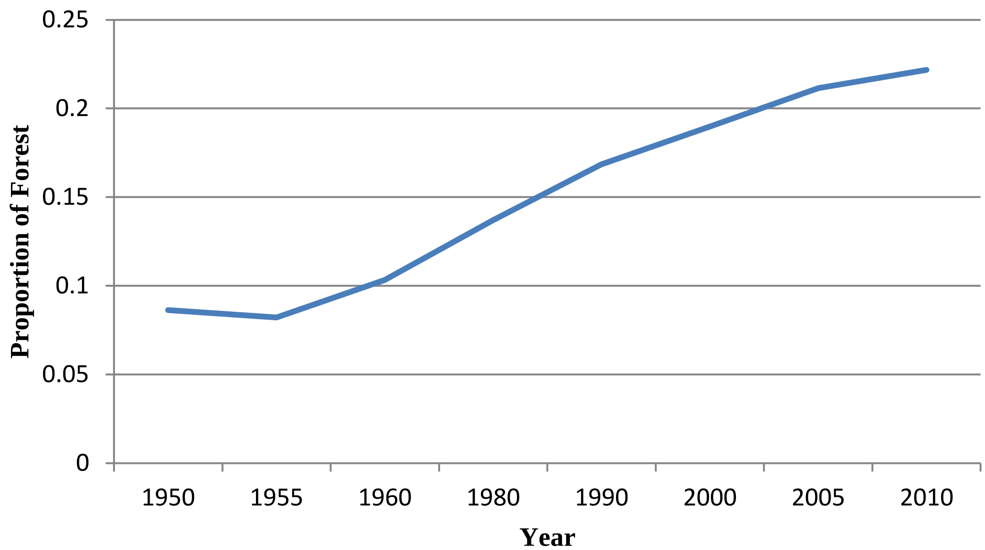
**Figure 1: Ireland and the United Kingdom**




### 4.4.2 China

China is a case that needed special consideration as well. The country has been plagued for decades by biodiversity losses and natural hazards, such as floods and desertification, caused by soil erosion and forest degradation (Wenhua, 2004). It therefore seems almost paradoxical that the FAO data shows that China has seen a vast increase in forest area between 1955 and 2010, where the proportion of forest area to total land area increased from 8.6% to 22.2%. Wenhua (2004) provides an explanation for why both of these sources might actually be accurate. He states that while many of China's natural forests have disappeared, causing severe forest degradation, there are large-scale planting operations funded or encouraged by the Chinese government. Plantations that exist for timber production are not included in the FAO data, but most of the plantations discussed by Wenhua are established as a result of the government's attempts to protect and conserve forests and are therefore not harvested for timber. These plantations are, however not very successful in restoring biodiversity and preventing soil erosion, which is why floods still occur frequently. The trend, shown in figure 2, presenting the FAO data might therefore be accurate, even though the increases in forest area are very high compared to most countries in the sample.

**Figure 2: China**




While most of China's observations are not regarded as outliers given the criteria specified, the underlying reasons for why the forest area increases so dramatically are quite different. Including China in the sample would weaken the support for an EKC for forest coverage because it is a country with relatively low income per capita and it experiences very high increases in forest coverage over the time span that is being investigated. Excluding China from the sample, may make the results stronger, but it would limit the extent to which the results can be generalized to China and countries that are very similar to China. Since China is not following a growth path that is consistent with most countries in the sample, it is removed from the sample.

### 4.4.3 United Arab Emirates, Brunei and New Caledonia

After removing all the outliers in the dependent variable, the income data showed three countries with exceptionally high income per capita levels. The United Arab Emirates; Brunei and New Caledonia, had considerably higher income levels than all other countries and showed an up-then-down pattern that was clearly different from all other income trends, that showed monotonically increasing trends. The United Arab Emirates' economy relied mainly on its high oil revenues until recently (Central Intelligence Agency, 2014c), which explains why it had one of the highest income per capita levels of the countries in the sample. Brunei has a similar economy, where extensive petroleum and natural gas fields are the main drivers of its GDP (Central Intelligence Agency, 2014a). New Caledonia, a former French colony until 1998, controls 25% of the world's nickel reserve and only has 267,840 inhabitants. This, in addition to substantial financial support from France, explains its relatively high income per capita level (Central Intelligence Agency, 2014b). While the income data seems to be correct, these countries were removed from the sample because they are clearly outliers compared to the rest of the countries. Additionally, the total forest areas of these countries, in 2010, was only 1.5 million hectares, which is about 0.00048% of the total forest area of all 105 countries in the sample in 2010, which means they only contribute minimally to the overall variation of the sample.

## 5. Results

The results of the model described above are presented in Table 5, which shows the results of the fixed effects and random effects estimations. Additionally, the result of the Hausman test, that tests the null hypothesis stating that the coefficients estimated in the fixed effects estimation are systematically different from the coefficients from the random effects estimation, is provided in the final row.

**Table 5: Final Model**

| Forest | Fixed Effects | | Random Effects | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| Income | -1.73e-06 | (2.64e-06) | -2.30e-06 | (2.52e-06) |
| $Income^2$ | 2.57e-10* | (1.26e-10) | 2.62e-10* | (1.24e-10) |
| $Income^3$ | -4.21e-15* | (1.95e-15) | -4.18e-15* | (1.93e-15) |
| Density | -.0012139*** | (.0002635) | -.0013691*** | (.0002267) |
| $Density^2$ | 1.87e-06** | (5.86e-07) | 2.23e-06*** | (5.39e-07) |
| $Density^3$ | -9.18e-10* | (3.86e-10) | -1.14e-09** | (3.64e-10) |
| Arid | . | . | -.4552664*** | (.0864236) |
| Semi-Arid | . | . | -.2648492*** | (.0593498) |
| Sub-Humid | . | . | -.1945407* | (.0846283) |
| Free | -.0047868 | (.0053823) | -.0056991 | (.0053721) |
| Partly Free | .0032687 | (.0044573) | .0028811 | (.0044788) |
| Income*Gini | -1.56e-07 | (1.77e-07) | -1.60e-07 | (1.74e-07) |
| $Income^2$*Gini | 1.26e-11 | (1.10e-11) | 1.24e-11 | (1.08e-11) |
| $Income^3$*Gini | -2.34e-16 | (1.81e-16) | -2.26e-16 | (1.79e-16) |
| Gini | .000428 | (.0006175) | .0005427 | (.0006145) |
| No Education 15+ | .0007542* | (.0003664) | .0007311* | (.0003363) |
| Constant | .401601*** | (.0285832) | .4719062*** | (.0352358) |
| | Includes time dummies | | Includes time dummies | |
| $R^2$ : | | | | |
| Within | 0.3877 | | 0.3863 | |
| Between | 0.0132 | | 0.3645 | |
| Overall | 0.0088 | | 0.3116 | |
| | | | | |
| # Observations | 372 | | 372 | |
| # Countries | 75 | | 75 | |
| | | | | |
| Hausman Test | $\chi^2$: | 9.31 | Prob > $\chi^2$: | 0.2309 |

Significance levels are indicated as: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Both regressions included time dummies for each year of data, 1975 – 2010, most of which are insignificant or very small and are therefore not reported. The table shows that the coefficients of the fixed and random effects estimations are roughly similar and have similar significance levels. The results of the Hausman test show that we cannot reject the null hypothesis at high significance, indicating that the random effects estimator is preferred over the fixed effects estimator. Results of an OLS, cluster robust estimation were considerably less significant and the income terms had the wrong signs, suggesting that random effects is the superior estimator.

The results above are based on the assumption that there is no heteroskedasticity or autocorrelation in the data. This assumption, as Stern (2003) indicates, is often invalid in EKC regressions that use panel data. Using robust estimates should eliminate any bias in the standard errors of the coefficients caused by heteroskedasticity. Autocorrelation can cause biased standard errors, as well as inefficient estimators. Using a clustered regression should adjust for any autocorrelation within units of the panel variable, i.e. within a single country (Cameron and Miller, 2013) and will also account for heteroskedasticity. The autocorrelation between countries has already been removed by using a fixed effects estimator and is therefore not a cause of concern. Table 6, below, shows the results of the autocorrelation test, as performed on the random effects model. The test results show that the null hypotheses can be strongly rejected, indicating that autocorrelation is present and needs to be adjusted for. The results of the robust, clustered estimation of the model are presented in table 7.

**Table 6: Testing for Autocorrelation in Panel Data**

| **Wooldridge Test for Autocorrelation in Panel Data** | |
|---|---|
| **$H_0$: No First-Order Autocorrelation** | |
| F(1, 95) | = 195.152 |
| Prob > F | = 0.0000 |

**Table 7: Robust, Clustered Estimation**

| Forest | Fixed Effects | | Random Effects | |
|---|---|---|---|---|
| | Coefficient | Std. Error | Coefficient | Std. Error |
| Income | -1.73e-06 | (4.16e-06) | -2.30e-06 | (3.99e-06) |
| $Income^2$ | 2.57e-10 | (1.98e-10) | 2.62e-10 | (1.94e-10) |
| $Income^3$ | -4.21e-15 | (2.75e-15) | -4.18e-15 | (2.70e-15) |
| Density | -.0012139 | (.000653) | -.0013691** | (.0004823) |
| $Density^2$ | 1.87e-06 | (1.22e-06) | 2.23e-06* | (9.84e-07) |
| $Density^3$ | -9.18e-10 | (7.04e-10) | -1.14e-09 | (5.99e-10) |
| Arid | . | . | -.4552664*** | (.053136) |
| Semi-Arid | . | . | -.2648492*** | (.0661891) |
| Sub-Humid | . | . | -.1945407** | (.0593128) |
| Free | -.0047868 | (.0071511) | -.0056991 | (.0074159) |
| Partly Free | .0032687 | (.0073457) | .0028811 | (.0075116) |
| Income*Gini | -1.56e-07 | (2.72e-07) | -1.60e-07 | (2.75e-07) |
| $Income^2$*Gini | 1.26e-11 | (1.50e-11) | 1.24e-11 | (1.50e-11) |
| $Income^3$*Gini | -2.34e-16 | (2.20e-16) | -2.26e-16 | (2.19e-16) |
| Gini | .000428 | (.0009684) | .0005427 | (.0009976) |
| No Education 15+ | .0007542 | (.0006868) | .0007311 | (.0006103) |
| Constant | .401601*** | (.05443) | .4719062*** | (.054917) |
| | Includes time dummies | | Includes time dummies | |
| $R^2$: | | | | |
| Within | 0.3877 | | 0.3863 | |
| Between | 0.0132 | | 0.3645 | |
| Overall | 0.0088 | | 0.3116 | |
| | | | | |
| # Observations | 372 | | 372 | |
| # Countries | 75 | | 75 | |
| | | | | |
| Hausman Test | $\chi^2$: | 9.31 | Prob > $\chi^2$: | 0.2309 |

* p<0.05, ** p<0.01, *** p<0.001

The coefficients in the robust, clustered estimation have not changed, as expected. The standard errors have increased and have made the income variables insignificant. The density variables are still somewhat significant and the presence of heteroskedasticity and autocorrelation have not completely undermined the support for a population density EKC. The results are less supportive of an income EKC, where joint significance tests indicate that the three income variables are jointly insignificant. The three density variables are jointly significant at the 1% significance level (p-value is 0.0066). Both regressions included time dummies for each year of data, 1975 – 2010, all of which are insignificant.

The results of the random effects estimation predict an inverted N-shaped curve for both income and population density. Using the coefficients of income and population density, the curves are graphed in figure 3 and 4. It is important to note that the time interval is drastically smaller than the availability of forest cover data. This is caused by the limited availability of data on a number of explanatory variables, such as income inequality and education.

**Figure 3: EKC (Income)**

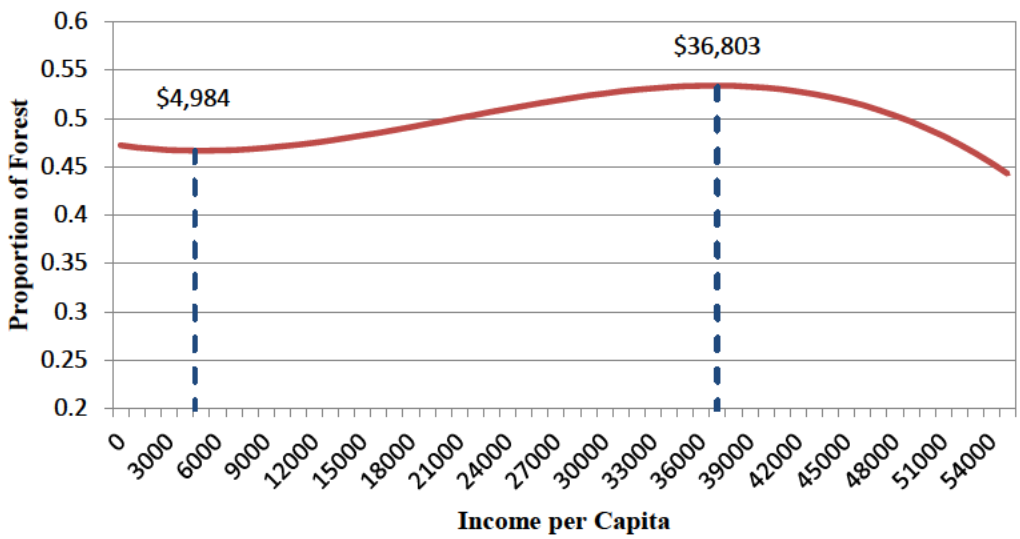
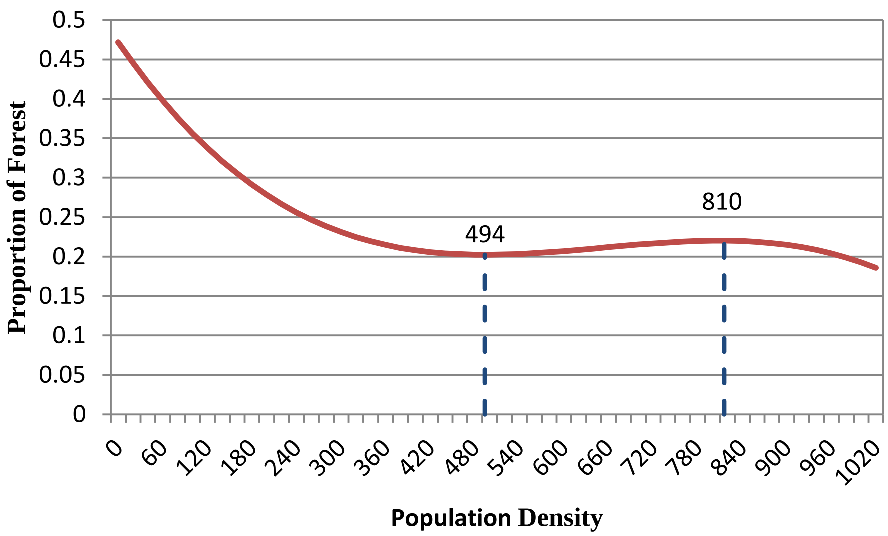


**Figure 4: EKC (Density)**




Note that income per capita is reported in International Dollars and population density is the number of people per square kilometers, where the maximum income level in the sample was ID$55,000 and the maximum population density level was 1020 people per square kilometer The turning points for income and population density are reported above the dashed lines in each graph. The curvature of graph 3 (income) is less pronounced than the curvature of graph 4 (density). However, the distribution of countries along the graph is more even for the income EKC than for the density EKC. In the income EKC graph, there are 44 countries whose income per capita in 2010 was below the first income turning point ($5,000). 46 countries were in between the first and second ($36,800) income turning point, and 6 countries had income levels that were higher than the second turning point. In the density EKC graph, 95 countries had density levels lower than the first turning point (494 people per square kilometers); 0 countries had density levels between the first and second (810 people per square kilometers); and 1 country had a density level above the second turning point. Almost all countries are therefore located before the first turning point.

The curves in figure 3 and 4 seem to suggest that forest coverage will decrease, increase and then decrease again as income increases. However, the number of countries that are located beyond the second turning point in both graphs is quite low. Since the number of countries that lie beyond the second turning point in the income per capita graph is relatively small, the second downward sloping portions of the graph should be interpreted with care. The cubed terms may be a better fit for the sample and the increase in forest coverage beyond the turning point may simply be leveling off. This leveling-off effect may be interpreted as a decline by the estimators. For the population density graph this means that the entire section of the graph beyond the first turning point should be interpreted with care and what is observed may simply be a downward sloping graph that eventually levels off. When the model is estimated with second-order polynomials for both income per capita and population density, the income per capita variables both become insignificant and have signs that are not consistent with an EKC. The density variables keep the same signs and significance levels in both specifications, making it harder to identify if the second or third order polynomial fits the data better. A separate functional form is therefore presented in table 8 of appendix B, presenting the results of the random effects estimation of the final model with a third-order polynomial for income and a second-order polynomial for population density. The accompanying population density EKC is presented in figure 5 of appendix A. This curve has a minimum of 702 people per square kilometers and there is still only 1 country with a population density level above this minimum.

It is clear from the results that the most significant variables in the model are the climate variables. Since these variables are dummy variables that don't change over the period examined, they can't be estimated with a fixed effects regression. They can be estimated with a random effects estimation, but this estimation introduces the assumption that all country-specific effects are drawn from a specific distribution and that none of the explanatory variables are correlated with any of the intercepts in the error term. According to the Hausman test, however, random effects was the superior estimator, allowing the climate variables to be included. All climate variables are highly significant and, as expected, show that the humid countries have higher intercepts than the countries with other climate types. Arid countries have the lowest forest coverage, followed by semi-arid and sub-humid countries, respectively. No conclusions can be drawn on the hyper arid countries because the only country in the sample with a hyper arid climate was not included due to limited availability of data. The intercepts for these countries, from lowest to highest are 0.195, 0.265, 0.455 and 0.472.

Three variables were included in the empirical model to analyze why a country might deviate from the socially optimal growth path of forest cover. The first was the political freedom variable, which has been split up into two dummy variables indicating whether a country was considered free in its political rights and civil liberties or only partly free, compared to the countries that were not free at all. Both variables are insignificant in the final model, indicating that there may be no significant effect of political freedom and civil liberties in the stock of forests. To assess whether there might be a delayed, or long-term effect of better political institutions on the stock of forests, lagged variables were introduced to the estimation, including a 10-year and 15-year lag. The results of these variables, however, were similar and both lagged variables were insignificant as well.

The second variable, attempting to estimate deviations from an optimal growth path, is the education variable that is expected to have a positive sign because more education may increase the awareness that forest conservation is important. Unfortunately, the variable was insignificant in the clustered estimation, indicating that there may be no relationship between education and the stock of forests. The potential of a squared or cubed relationship between education and forest coverage was investigated to assess a non-linear relationship, but neither was shown to be significant and the linear term was consistently negative and insignificant.

The last group of variables capturing deviations from the optimal growth path are the interaction terms between the income per capita variables and the income inequality variable (Gini coefficient). The income variables in these estimates show the partial income effect at the mean level of income inequality (Gini coefficient is 36.5). While the coefficients indicate that higher income inequality increases the variability of any observed EKC, the fact that the coefficients are insignificant, doesn't allow one to draw any definitive conclusions about the effect of income inequality on the slope of an EKC.

One disadvantage of the final model presented above is that the number of observations has decreased significantly compared to a reduced form estimation of the model. Estimating the reduced form model may yield stronger evidence for an EKC because it estimates the total effect of income per capita and population density on forest cover and because there is more data available. The disadvantage of estimating the reduced form model is that we may introduce omitted variable bias, which leads to an over- or underestimation of the coefficients. Table 13 in appendix B presents the results of the clustered estimation of the reduced form model. The results show that the density variable are highly significant and the income per capita variables have become more significant as well, though they are jointly insignificant. The density variables are still jointly significant, now at the highest significance level. The reduced form estimation has therefore not provided significantly stronger evidence in favor of an EKC for both income per capita and population density.

## 6. Discussion

The results presented in this thesis provide some evidence in support of the theory behind the EKC, but its significance is quite limited. The main variables of interest are income per capita and population density. While the population density variables show some significance at a 5% significance level, the income per capita variables are individually and jointly insignificant. However, the population density variables are jointly significant at the 1% significance level. This result is not inconsistent with the general literature on the EKC, as empirical evidence supporting a growth path of environmental quality consistent with an EKC is mixed. A possible explanation for the limited significance of the income per capita and population density variables is the quality of the data, specifically the data in the FAO's FRA reports. Grainger (2007) notes that the inconsistencies between reports raises questions about the reliability of the FAO data. This inconsistency was apparent after about half of all countries reported by the FAO had to be dropped from the sample due to missing or unreliable data. A more complete dataset, covering a wider range of countries, would have increased the sample size, which may have yielded stronger and more conclusive results. Nevertheless, the 96 countries in the sample were relatively diverse based on their respective locations along the estimated EKC curve for income per capita. This is encouraging because it ensured that most stages of economic development were represented in the sample. Additionally, the fact that the analysis does not find strong evidence for a single EKC, does not refute the possibility that each country might have its own growth path, which may or may not be consistent with an EKC.

A number of other explanatory variables were included in the analysis, some of which proved to be quite significant. Some of these variables provided insights into the theoretical underpinnings of the EKC literature, especially why a country might deviate from the optimum growth path of forest cover (predicted by theory) and what this might mean for the possibility of observing an EKC. The first were the political freedom variables, which were insignificant and failed to show evidence supporting the notion that more political freedom improves the effectiveness of institutions that are in place to protect and conserve a country's resources. The second variable measuring the possibility of deviating from an optimal growth path was the education variable. The results of this variable did not support the idea that better education translates into better awareness of the importance of forest conservation. Though the variable was insignificant, the results showed that as education improved, forest cover tended to decrease, rather than increase. The reasons for this result may simply be that the measure of education used was too crude. Quality of education, measured by the percentage of people (age 15+) without a primary school education, improved in virtually all countries in the sample over the time period analyzed. Perhaps more specific measures of education, or better yet awareness, would have yielded different results. An example may be voting preferences on environmental issues or per capita donations to groups that promote environmental awareness. The last group of variables estimating the possibility of deviating from the optimal growth path were the income inequality interaction terms. Before adjusting for heteroskedasticity and autocorrelation, the results suggested that income inequality may be detrimental to forest cover at all stages of economic development, creating curves that had more extreme minima and maxima. However, the results of the clustered estimations suggested that these effects were insignificant. It is important to note, however, that the sample size of the final model decreased considerably due to limited availability of these three variables and a longer dataset may show different results.

The results also show the effect of climate types of forest coverage. Climate appears to be an important indicator of forest endowments, and results were consistent with the literature stating that humid climates are more suitable for forest growth. Climate types had considerable explanatory power over the differences (fixed effects) between countries as was evident in the significant increase of the 'between $R^2$. Climate types should therefore always be considered when analyzing the development of forests over time and space.

Though the results of this thesis don't offer much support for a growth path of forest cover that is consistent with an EKC, results to the contrary would not have presented economic growth as a solution to decreasing environmental quality. Arrow et al. (1995) stress the importance of this by stating that, if anything, results consistent with an EKC show that it may be desirable for economic growth to be accompanied by stricter policy reforms. This leads back to the theoretical underpinnings of the EKC, that clearly shows that an EKC growth path is not the definitive optimal growth path predicted by theory. Theory suggest that, given a set of strict assumptions, the optimal growth path may be consistent with an EKC, but this is not the only optimal growth path for forests. Additionally, there are many factors that, beyond a theoretical analysis, might cause a country's growth path of environmental quality to stray from what is socially optimal. Policy makers should therefore be careful when they interpret results of EKC analyses and should base policy decisions on actions that have actually shown to be successful in improving environmental quality.

## 7. Conclusion

This study set out to analyze if there is evidence of a growth path of forest cover consistent with an Environmental Kuznets Curve for forest coverage. The Environmental Kuznets Curve shows the relationship between a country's income per capita and a measure of environmental quality. The analysis in this thesis additionally covered the relationship between environmental quality and population density, which may exhibit the same relationship. The measure of environmental quality that was used to test these relationships empirically was the share of land in forests. The main question that this thesis attempts to answer is therefore: Is there a U-shaped relationship between income per capita and the share of land in forests? The theoretical model described provided a set of conditions under which the optimal growth path of forest cover may be consistent with the U-shaped path of an EKC. The empirical analysis attempted to estimate this relationship but only found limited evidence that we actually observe this curve in the data. The model that was estimated included third order polynomials for both income per capita and population density to assess whether we observe non-linear relationships. The results of the model showed that the income per capita variables were both individually and jointly insignificant. Only the squared and cubed population density variables were significant, but all three population variables were jointly significant at the 1% significance level. Evidence in favor of an EKC for income per capita is therefore quite weak, while there is some support for an EKC for population density. Despite the limited significance of these variables, the results allowed us to estimate the observed EKC curves with the following turning points. The observed EKC for income per capita has a turning point at ID$5,000 and at ID$36,800 The observed EKC for population density has a turning point at 494 and 810 people per square kilometer.

Though the results were inconclusive, the evidence gathered was insufficient to refute the possibility of a growth path of environmental quality consistent with an EKC. Arrow et al. (1995) note that evidence in favor of an EKC for a specific indicator of environmental quality, is not sufficient to conclude that environmental quality as a whole follows an EKC as well. This warning can be applied to the results of this thesis as well, where the inability to find conclusive evidence in favor of an EKC for forest cover is not sufficient to conclude that an EKC for other indicators of environmental quality does not exist either. This story is consistent with the literature, where evidence on the existence of an EKC for a wide variety of environmental quality indicators is mixed. Policy makers should therefore be cautious about drawing any conclusions based on the relationship predicted by the EKC and should be aware that, whether an EKC exists or not, economic growth is not a recipe for improved environmental quality, such as forest cover. It is clear that the present state of the world's forests is an important and complex environmental problem that requires more than research on the EKC alone to resolve.

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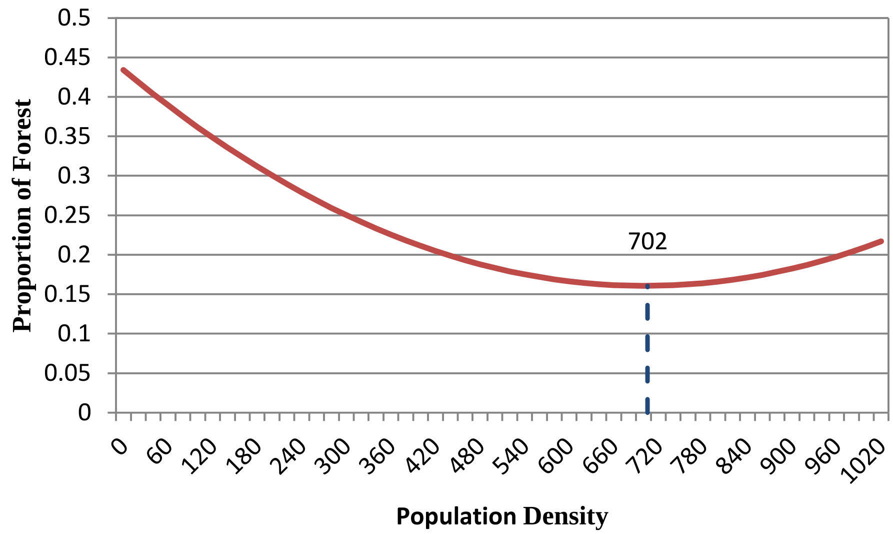
**Appendix A (Figures)**

**Figure 5:EKC Density (Second-Order Polynomial)**



## Appendix B (Tables)

### Table 8: Functional Form (Second-Order Polynomial)

| Forest | Random Effects | |
|---|---|---|
| | Coefficient | Std. Error |
| Income | -6.97e-07 | (3.67e-06) |
| Income$^2$ | 2.33e-10 | (1.92e-10) |
| Income$^3$ | -4.03e-15 | (2.72e-15) |
| Density | -.000779 | (.0002455) |
| Density$^2$ | 5.55e-07 | (1.74e-07) |
| Arid | -.4236666 | (.0457015) |
| Semi-Arid | -.2418082 | (.064594) |
| Sub-Humid | -.1870719 | (.0639359) |
| Free | -.0033605 | (.0081182) |
| Partly Free | .0035039 | (.0079047) |
| Income*Gini | -1.34e-07 | (2.70e-07) |
| Income$^2$*Gini | 1.16e-11 | (1.49e-11) |
| Income$^3$*Gini | -2.23e-16 | (2.18e-16) |
| Gini | .0004689 | (.0009581) |
| No Education 15+ | .0008729 | (.000661) |
| Constant | .4339967 | (.0451677) |
| | Includes time dummies | |
| $R^2$ : | | |
| Within | 0.3737 | |
| Between | 0.3280 | |
| Overall | 0.2793 | |
| | | |
| # Observations | 372 | |
| # Countries | 75 | |

**Table 9: Reduced Form**

| Forest | Random Effects | |
|---|---|---|
| | Coefficient | Std. Error |
| Income | -4.72e-06 | (4.28e-06) |
| $Income^2$ | 3.45e-10* | (1.71e-10) |
| $Income^3$ | -4.72e-15* | (2.05e-15) |
| Density | -.0027303*** | (.000435) |
| $Density^2$ | 5.79e-06*** | (1.23e-06) |
| $Density^3$ | -3.49e-09*** | (8.58e-10) |
| Constant | .5020487*** | (.0374922) |
| | Includes time dummies | |
| $R^2$: | | |
| Within | 0.4859 | |
| Between | 0.0166 | |
| Overall | 0.0368 | |
| | | |
| # Observations | 775 | |
| # Countries | 96 | |