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Ph.D. Thesis

Economic growth and the Forest Development Path

A re-assessment of the Environmental Kuznets Curve for deforestation

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To my parents, always present and supportive
and my uncle Nicola

Este es el bosque
Y aquí, un momento,
Mi corazón espía…
Van y vienen
Los descendientes de los árboles
—escondidos animales geométricos.
Se meten en sus cóncavas materias
—sienes aéreas,
Largos fantasmas de alas sumergidas.
Se despliegan,
gravitan contra la sombra,
ciertas partes ascendentes,
del poderoso y habitante oxígeno.
Este es el bosque desprendido
y aquí, en esta forma de sed
pongo mi corazón a descansar,
a descansar,
un pensamiento de hojas que fue mío.
Aquí, sobre la tempestuosa apariencia,
de una campana lanzada por la hierba.
Este es el bosque
y aquí mi corazón, desanudándose,
sólo es un ruido,
una alegría que se desvió por dentro,
y se perdido incesantemente,
y no puede encontrarse,
o siquiera parecerse a sí misma.
Aquí mi corazón
—este es el bosque—,
reposa celebrando su partida.

Abstract

This research attempts to answer to one of the unresolved questions in forestry economics according to Hyde (2014), the possible existence of an *Environmental Kuznets Curve for deforestation*. It will be shown how this curve could be re-conciliated with the famous *Forest Transition* hypothesis of Mather (1992) and even with the competing land use model *à la* von Thünen of the *Forest Development Path* proposed by Hyde (2012). The investigation is conducted by means of a cross-country analysis for 114 countries. Forest cover data has been specifically reconstructed based on the last *Forest Resource Assessment* of FAO (2015). Countries have been clustered into low, middle, and high income economies and panel data techniques, both statics and dynamics, have been implemented. Results conclude for a U-shape curve for low and high income (in this group for reforestation) while a reverse U-shape for middle income economies. However, despite the functional form is preserved among the three groups, turning points change according to model specifications.

Keywords: Environmental Kuznets Curve, Forest Transition, Panel Data
JEL Classification: C23, Q23, Q56

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List of Abbreviations

CO_2	Carbon dioxide
NO_x	Nitrogen oxides
SO_2	Sulfur dioxide
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
BIC	Bayesian Information Criterion
CADF	Cross-sectional Augmented Dickey-Fuller
CDIAC	Carbon Dioxide Information Analysis Center
CFC	Chlorofluorocarbons
CO	Carbon monoxide
COP	Conference of Parties
CS-ARDL	Cross-sectionally augmented Autoregressive Distributed Lag
DR	Deforestation Rates
DSDM	Dynamic Spatial Durban Model
EDI	Environmental Degradation Index
EKC	Environmental Kuznets Curve

EKCd	Environmental Kuznets Curve for deforestation
EPA	US Environmental Protection Agency
FAO	Food and Agriculture Organization of the United Nations
FDP	Forest Development Path
FE	Fixed effects
FF	Fudge Factors
FGLS	Feasible Generalized Least Squares
FRA	Forest Resources Assessment
FT	Forest Transition
GDP	Gross Domestic Product
GEMS	Global Environmental Monitoring System
GHG	Greenhouse gas
GMM	Generalized Method of Moments
GNI	Gross National Income
GRA	Gross Rent for Agriculture
GRF	Gross Rent of open access Forest use
GRRFM	Gross Rent of Responsible Management Forest
GWR	Geographically Weighted Regression
HDI	Human Development Index
HRU	Homogeneous Response Units
IEA	International Energy Agency
IFL	Intact Forest Landscape
IMF	International Monetary Fund
INSCR	Integrated Network for Societal Conflict Research

IPEA	Brazilian Institute of Applied Economic Research
LOWESS	Robust locally weighted scatter plot smoothing
MCAs	Minimum Comparable Areas
MG	Mean Group
MODIS	Moderate Resolution Imaging Spectroradiometer
NAFTA	North American Free Trade Agreement
NFI	National Forest Inventory
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
ORNL	Oak Ridge National Laboratory
PES	Payments for Ecosystem Services
PMG	Pooled Mean Group
PPCDAm	Action Plan for the Preservation and Control of Deforestation in the Legal Amazon
PPP	Purchase Power Parity
PRODES	Satellite monitoring of the Brazilian Amazon rainforest
PSTR	Panel Smooth Transition Regression
RE	Random effects
REDD+	Reducing Emissions from Deforestation and forest Degradation plus conservation, sustainable management of forests, ad enhancement of forest carbon stocks
RMC	Random Coefficient Model
SAPs	Structural Adjustment Programmes
SDGs	Sustainable Development Goals
SFM	Standards for Forest Management

SPM	Dark matter suspended
TFAP	Tropical Forestry Action Plan
TP	Turning Point
UN	United Nations
UNECE	United Nations Economic Commission of Europe
UNEP	United Nations Environmental Program
UNFCCC	United Nations Framework Convention on Climate Change
US	United States of America
USSR	Union of Soviet Socialist Republics
WB	World Bank
WRI	World Resources Institute

Introduction

FORESTS represent the beating lung of our living planet, the sustenance for all living-beings where mankind could represent both a guardian or a curse for them. Thus, the relationship between society's development and the role of forests requires special attention in order to gather pertinent policy implications. Observing the history of Western countries and their forest cover area, Mather (1992) speculated for a possible *Forest Transition* hypothesis (FT) where countries switch from a negative to a positive forest cover change. In the same year, the *World Development Report* (WB, 1992) stressed how economic growth and the environment are not negatively related but able to go hand-in-hand, at least after a certain level of income per capita. This assertion represented the ground-floor for the so-called *Environmental Kuznets Curve* (EKC) which hypothesizes an inverted U-shape relation between economic growth and environmental degradation. However, among the broad literature which characterizes the EKC, deforestation hosts a relatively small role with conflictual results representing one of the twelve unresolved issues in forest economics (Hyde, 2014). Therefore, this work attempts to provide an answer for this issue starting from the *Forest Development Path* (FDP) proposed by Hyde (2012) which investigates the competing land use between agricultural and forest land along three phases of economic development. In the first two phases, forests will be drowned down and eventually start to grow again in the late third phase or rather flowing into a potentially fourth phase characterized by forest cover restoration.

Chapter 1 carries out an extensive literature review of the EKC with a prominent focus for the *EKC for deforestation* (EKCd) stressing both strengths and flaws of this hypothesis. Moreover, it will be shown how the the EKCd and the FT could be investigated *vis-à-vis*, linked by the various phases of the FDP. Along this reconciliation of theories, the proposed EKCd is slightly different to what could be found in the "classic" literature of the EKC. In fact, differently from pollutants such as CO_2, in the case of deforestation it is possible to observe even an end of the environmental degradation (*i.e.* deforestation rates), then the achievement of the FT. Therefore, after the peak or turning point of the EKCd and the level of zero deforestation, the curve should continue in a process of forest restoration. Here deforestation rates become negative and it is possible to speculate another turning point corresponding to the maximum reforestation rate.

Since a proper investigation of the EKCd requires cross-country forest cover data with a consistent time-span, Chapter 2 attempts to reconstruct this data considering both developed and developing countries, starting from the last *Forest Resources Assessment* of FAO (2015). Only countries with at least 1 million of hectares of forest coverage in 2000 have been selected to reduce heterogeneity among them. The reconstruction has been performed for three categories of forests: total, natural, and planted forest. The result is an unbalanced panel of 114 countries with a maximum time coverage of 55 years (1960–2015).

Eventually, Chapter 3 employs this reconstructed data to investigate the possible existence of the EKCd performing a cross-country analysis by means of static and dynamic panel data techniques. Countries have been clustered into three groups: low, middle, and high income economies. Results identified a U-shape curve for low income, a reverse U-shape for middle and, again, a U-shape even for the high income group. Therefore, for the middle income group—which is also the largest among the three—the classical shape of the EKCd seems to be verifiable. As concern the other two groups, wile for low income results suggest an increase of forest depletion with higher GDP levels, in the case of high income economies, the peak has to be referred to reforestation rates since most of these countries are in a phase of forest restoration (the second turning point of the suggested EKCd). Nonetheless, despite the three functional forms are preserved among the performed models (both static and dynamic, with and without the addition of control variables), the turning points obtained are quite mixed, especially for the middle income group.

In conclusion, despite the EKCd seems to be cautiously verifiable in the case of deforestation, it cannot be considered yet a complete resolved question since results are not homogeneous, then able to provide clear policy recommendations. However, this research should represents a new fresh-start, both in terms of data and methodology, to broaden a branch of the EKC literature excessively scant and understudied.

1 Economic growth and the environment

It is not so much for its beauty that the forest makes a claim upon men's hearts, as for that subtle something, that quality of air that emanation from old trees, that so wonderfully changes and renews a weary spirit.

Robert Louis Stevenson

THE relationship between environment and economic growth has always been a touchy necessary coexistence throughout history and several events showed how the importance of the former spurred the inevitable actualization of policies among modern societies to protect natural resources and reduce air and water pollution—and eventually, to ensure the latter. For example, the sadly famous "Great Smog" which distressed the city of London in 1952 provoked more than 12,000 fatalities and resulted in the unavoidable necessity to adopt, four years later, the Clean Air Act which put in place measures to reduce air pollution due to intensive use of charcoal (Davis, 2002). Awareness about tropical deforestation dates back even further, more than 165 year ago, during the so-called "denudation crisis" in India which raised unease in Eastern colonies of the British Empire due to timber and fuelwood shortages. In fact, since the middle of nineteenth century[1] the fear of a "timber famine" overspread in Western countries and their overseas colonies. Furthermore, at the beginning of the last century, the two geographers Alexander Woeikof and Ernst Friedrich stressed how the civilization and global expansion of these countries relied on a detachment between man and earth within a destructive

[1] In 1866, Andrew Fuller first sounded this alarm saying: "the day is coming", the same year when the German biologist Ernst Haeckel coined the world "ecology" (Williams, 2003).

economy on natural resources. In the same period, French colonial officers pointed out the necessity to address dry-land forest losses in West Africa (Williams, 2003; Seymour and Busch, 2016).

However, this awareness for the environment, especially forests, did not lead to an end or slowdown of the depletion. During the mid-eighties problems of tropical deforestation came back to the forefront with concerns for the fate of the Brazilian Amazon which lead to the implementation of the Tropical Forestry Action Plan (TFAP) by FAO in 1985,[2] but while the general attention for global warming rises, mainly focused on containing carbon dioxide (CO_2) emissions, attentions for tropical forests faded away. During the 1992 Earth Summit in Rio de Janeiro, negotiations failed in reaching a forest convention and only in recent years attention for forests has been "catapulted back" at the top of government's climate agenda after the discovery of their importance in fighting climate change. Therefore, with the necessity to avoid an increase of global temperature up to 1.5 °C and achieving the goal of "zero emissions" declared in the 2015 Paris Agreement within the United Nations Framework Convention on Climate Change (UNFCCC),[3] attention to global forest-use and appropriate policies to reduce deforestation are paramount in a world of continued population and economic growth (Seymour and Busch, 2016).

From an academic perspective, during the early seventies two fundamental and opposite orientation ruled the debate between economic growth and environmental protection.[4] The Club of Rome was flag carrier of the "growth limit" motto, pointing out how the limited resources of the planet in the long run cannot sustain the overwhelming economic growth. Therefore, they asked for a reduction of this latter target in favor of more environmental protections (Meadows *et al.*, 1972).[5] On the other side, there was Beckerman (1992)[6] followed, at the end of the decade, by Dasgupta and Heal (1979) which enlightened this dichotomy as a possible complementar-

[2] Two years later, the famous Brundtland Report introduced the concept of sustainable development (WCED, 1987).

[3] Also called COP 21, it was the 21st session of the Conference of the Parties (COP) since the first one in 1992 (the Earth summit of Rio de Janeiro).

[4] For example, the book of Barton (2002) retraces the origins of the environmentalisms, especially concerning forestry.

[5] Also the though of Georgescu-Roegen (1971) is included in this position.

[6] Beckerman's standpoint is usually summarized with his famous statement: "[t]here is clear evidence that, although economic growth usually leads to environmental deterioration in the early stages of the process, in the end the best—and probably the only—way to attain a decent environment in most countries is to become rich." (Beckerman, 1992)[p.482].

ity, thus the chance to have increasing economic wealth without an unavoidable environmental worsening.[7]

In 1992, the World Bank's *World Development Report* pointed out how economic growth is not necessarily related to an environmental degradation arguing that "[t]he view that greater economic activity inevitably hurts the environment is based on static assumptions about technology, states, and environmental investments." In fact, "[a]s incomes rise, the demand for improvements in environmental quality will increase, as will the resources available for investment" (WB, 1992)[p.38–39]. This assumption was based on the study for this report conducted by Shafik and Bandyopadhyay (1992) and their conclusion stated how economic growth initially is related with an increase in environmental degradations, consequently, after a certain threshold, the trend diverts. A conclusion derived from the primer work of Grossman and Krueger (1991) conducted to investigate possible environmental implications of the North American Free Trade Agreement (NAFTA). The result is an inverse U-shape relation between economic growth and environmental degradation named *Environmental Kuznets Curve* (EKC) due to its assonance with the similar relation proposed by Kuznets (1955) between income inequality and economic growth (Panayotou, 1992). After these pioneering works, many others followed, and still do, establishing the EKC as one of the core theories in environmental economics—all but without critics (*e.g.* Stern, 2004).

When applied to forests, the EKC speculates that increasing levels of economic growth are first associated with a rise of forest loss and thus deforestation rates but, after a peak, deforestation rates slowdown until reaching a positive forest cover change. This path lead to an undoubted assonance with the *Forest Transition* (FT) hypothesis firs proposed by Mather (1992) which affirms how countries along their history first experience a forest loss and then a recovery. However, although the EKC's literature is almost boundless, studies which focus on the relation between GDP and deforestation are still few and scant if compared with other environmental indicators (first among all CO_2). In fact, Hyde (2014) stresses how the possible

[7] As rightly recalled by Carson (2010), this debate generated the famous IPAT equation which relates Environmental Impacts (I) to Population (P), Affluence (A), and Technology (T). The idea was that population growth linked with affluence (commonly proxied with GDP per capita) represents the main factors that lead to an environmental degradation. Conversely, Technology has a neutral or positive role. From this idea, some economists engaged the debated with other different positions (*e.g.* Kneese and Ridker, 1972; Nordhaus, 1973; Solow, 1973). Furthermore, in addition to the famous IPAT equation, of equal importance is the KAYA identity which deals with a subset of GHG emissions: carbon dioxide (CO_2). Those emissions are expressed as the product of population, GDP per capita, energy intensity (energy/GDP), and intensity of energy (emissions/energy) (Kaya, 1989; IPCC, 2015).

existence of an EKC for deforestation still represents one of the twelve unresolved questions for forest economics. Therefore, seeking to answer this inspiring inquiry, a theoretical and analytical re-assessment of this hypothesis seems to be necessary.

The following chapter starts from the importance of forests and tries to reconcile and give support through an unique theoretical foundation the *EKC for deforestation* (EKCd) with the FT. The land-use model proposed by Hyde (2012), which explains the competing role between agricultural and forest lands throughout the economic development could represent the junction ring between these two theories as well as a cautious justification for the existence of the EKCd. Therefore, these three theories are here presented with a particular focus for the EKC's literature and its application to the deforestation problem.

1.1 The importance of forests

Forests represent the beating lung of our living planet, the sustenance for all living-beings where mankind could represent both a guardian or a curse for them. At the beginning of the last century, in his famous book *Economic of Forestry*, Bernard Fernow (1902) was already stressing this prominent relation: "[t]he natural resources of the earth have in all ages and in all countries, for a time at least, been squandered by a man with a wanton disregard of the future, and are still being squandered wherever absolute necessity has not yet forced a more careful utilization" [p.1]. Furthermore, through an historical perspective, forests represent the "earliest world of mankind" and a primal element which has favored and spurred the evolution of primitive societies and whose absence could have potentially represented a threat for them (Fernow, 1913).[8] Forests' contribution to evolution continued until modern societies and countries—and still does.

Forests host the greatest amount of biodiversity in the world, home of 80% of land animals and plants, and provide essential environmental services such as clean water supply, resilience against disasters, recreation, cultural, and spiritual activities (FAO, 2016). Due to all of these aspects and more, forests fulfill a core role in achieving the new Sustainable Development Goals (SDGs) of UN (2017).[9] Thus,

[8]For example, the extinction of indigenous population in the Chilean island of Rapa Nui (also knows as Easter Island) has always been attributed to fierce and heinous deforestation. However, a recent study of Stevenson *et al.* (2015) refuted this theory.

[9]The SDG number 15, "Life on land", is the one more closely related to forests where targets 15.1 and 15.2 refer to forests and sustainable forest management (FAO, 2017b).

the relation between countries development and the role of forests requires special attention in order to gather pertinent policy implications.

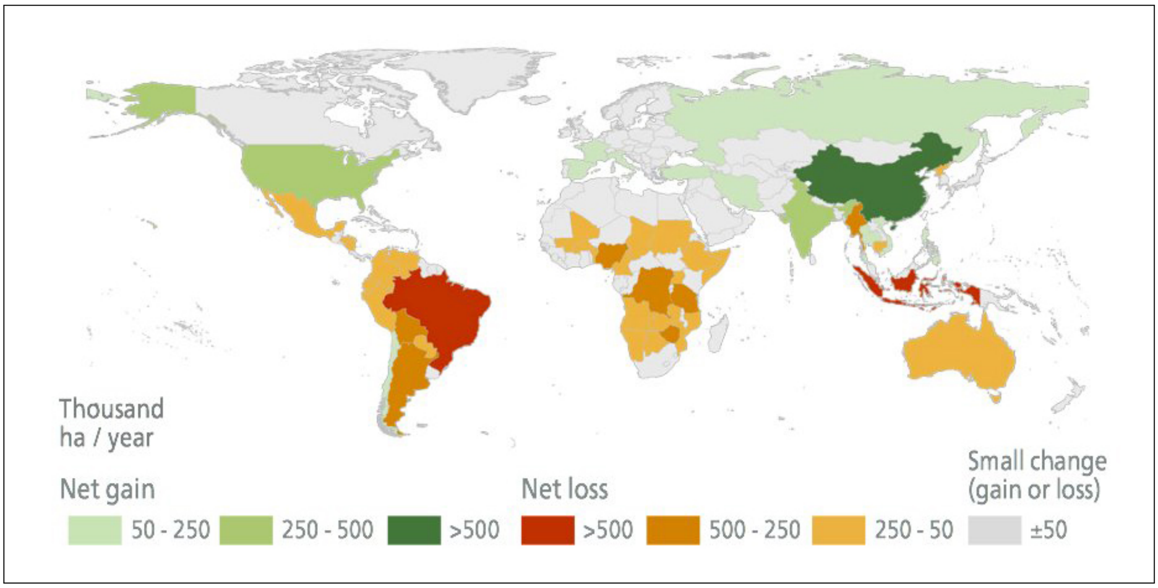
Among others, the implementation of the REDD+ initiative[10] represents a core tool to put into place properly, aware of countries' economic level of development and forestry sector, to effectively achieve a reduction in emissions through deforestation control—an action likely able to cut down greenhouse gas (GHG) emissions up to 30% (Goodman and Herold, 2014). The REDD+ initiative is an international framework agreement aimed to introduce deforestation reduction as one of the tools to reduce emissions that cause climate change. It serves as a mechanism where industrialized countries commit themselves to provide support to developing countries—those more affected by the deforestation phenomenon and climate change—in order to achieve a sustainable reduction in forest loss on behalf of management forest activities. This mechanism has been created during the Bali (2007) and Copenhagen (2009) COPs of UNFCC (UNFCCC) with the aim to preserve world's remaining primary forests. During the Poznan meeting of 2008, REDD changed its name into REDD+ with a widening of the mechanisms activities while with the 2015 Paris Agreement the role of REDD+ has been endorsed. Currently 64 developing countries among Africa, Asia-Pacific, and Latin America and the Caribbean are obtaining support from this program (Leblois *et al.*, 2017; Seymour and Busch, 2016).[11]

Nowadays forests cover a surface of almost 4,000 millions of hectares and an encouraging slowdown in deforestation rates can be observed at global level, from 7.3 million he/year of the period 1990-2000 to 3.3 million. In spite of this, over the last 25 years an area of 129 million he of forest, approximately equivalent to South Africa, have been lost and each year an area larger than Luxembourg disappears. Figure 1.1 shows annual forest cover gains and losses over this past quarter of century and colors clearly evidence how the South tropical areas, especially Sub-Saharan Africa and Latin America, suffered the main losses while North temperate and boreal zones showed an opposite trend. This pattern stresses an undeniable North-

[10]The acronym REDD+ sands for Reducing Emissions from Deforestation and forest Degradation plus conservation, sustainable management of forests, and enhancement of forest carbon stocks (UNFCCC, 2017).

[11]This mechanisms is substantially characterized by three phases. In the first phase, countries have to define and submit their national strategies to reduce deforestation and they have to qualify themselves to obtain grants (the Warsaw COP of 2013 identified qualifies that countries have to comply with in order to be eligible). In the second, partner countries have to implement their strategies while in the third and last phase countries will receive payments based on their performances in attain their targets (Leblois *et al.*, 2017; Seymour and Busch, 2016).

Figure 1.1 *Forest area annual net change (1990-2015)*



Source: FAO (2015).

South dichotomy reflected also by huge differences in economic growth between these two areas. In fact, low and middle income countries during the considered time frame losses around 150 million he while high income countries gained more than 19 million he of forest cover (FAO, 2015; WB, 2017). Moreover, it must be mentioned the fact that forest losses are being replaced by increasing amount of forest plantations (from 3% of total forest in 1990 to 7% in 2015), especially in China and India, implemented for erosion control and fuelwood production, or Brazil, Indonesia, and Chile which host the largest industrial plantation sites. However, forest plantations are not full substitutes to natural forests, especially in terms of biodiversity and carbon reservoirs (FAO, 2015; Palo *et al.*, 2000).[12]

All things considered, the importance given to forests and their global trends requires remarkable attention chiefly from a sweeping economic perspective, especially for tropical developing countries (FAO, 2016). Therefore, macro-analysis relations conducted under the EKC's framework could be proper procedure to assess this matter.

[12]As concern forest plantation and reforestation processes Williams (2003) stressed out how their positive numbers and trends are often optimistically overrated.

1.2 From von Thünen to Kuznets

The title of this section, linking these two personality, divided by 50 years between the death of the first[13] and the birth of the latter[14] could sound of hard to understand. However, a red path between these two names could be traced linking the famous von Thünen's land-use model to the application of the Kuznets curve to the case of deforestation. The lining connection between the two authors could be founded in the seminal work of Hyde *et al.* (1996), then in-depth in Hyde (2012) in a so-called *Forest Development Path* (FDP). von Thünen's description of economic geography made 1826 in his famous *Isolated State*[15] has been used by Hyde *et al.* (1996) to develop a simple model able to catch the competitive use of land between agriculture and forest, then enlarged into a three-phases model which describe the evolution in the use of the forestry sector during the economic growth of a country. During these three stages it is possible to see how the value of forestland grows and competes with agriculture first increasing deforestation and then, with the gradual emergence of managed forest and further increase of forest product values, a return in the total amount of forest cover as percentage of forestland.

Kuznets is commonly considered the developer of the modern concept of Gross Domestic Product (GDP)[16] and in his famous work of 1955 he proposed an inverted U-shape relation between GDP growth and income inequality: first stages of income growth are associated with a specular increase in inequality, but after a certain level of GDP this relation detaches and as income continues to grow, inequality shall reduce. This hypothesis has been commonly known as *Kuznets Curve*. Later, at the beginning of the nineties, Grossman and Krueger (1991) first applied this relation to the environment. Further developments of their pioneering work would have given birth to the famous EKC: the hypothesis that environmental degradation first increase with economic development, but after a certain threshold, this negative relation diverts and further increases of income will be associated with a reduction in pollution and natural resources depletion or a general increase in environment quality. The EKC has been applied also to the use of forest trying to evaluate if economic growth and deforestation are related by an hump-shape curve relation.

[13] Johann Heinrich von Thünen (1783–1850).
[14] Simon Smith Kuznets (1901–1985).
[15] A review of von Thünen's theory could be found in the work of Samuelson (1983).
[16] He developed the definition of GDP for a US Congress report in 1934. However, he warned against the use of this indicator ad a measure of welfare.

In the same years of early works about EKC and the growing debate about the enviroment, another theory emerged: the FT hypothesis first proposed by Mather (1992). He substantially showed how countries in their history and development first degraded and used forest resources to lead their growth, then eventually, during this path a switch point occurs, where forest cover starts to rise again. However, albeit different, the EKC for deforestation and the FT are two similar theories which could be seen cautiously as two faces of the same coin. On the one hand the FT, where the relation between forest cover and time follow a U-shape relation; on the other the EKC, where deforestation and GDP are possibly linked by a reverse U-shape relation. Obviously those are relations which relies on empirical evidences and require a long time span to be verified and for sure not exempt from criticisms.

Withal, the three-stages model of the FDP proposed by Hyde (2012) is similar to the EKC for deforestation—therefore, with the FT as well.[17] They both evidence a first phase of low forest degradation followed by a second period where the development of countries raised and the value of forest land as well increasing deforestation and later on the creation of managed forest. In the third phase managed forest continues to increase spurred by the growing forest value and natural forests recover since forest products are substitute with other non-forest inputs and, eventually, non-market values and non-consumptive ecosystem services of forests sustain their preservation. The author himself suggests this connection stating that "the hypothesis that the development process begins with forest exploitation but eventually, after some level of development, the incentives for forest exploitation shift and forests and their associated natural environments begin to recover" (Hyde, 2012)[p.234]. Therefore, here lies the connection between von Thünen and Kuznets. The framework of economic geography of von Thünen, used as ground-floor in the theory of the FDP of Hyde (2012) follows the reverse U-shape relation between economic growth and deforestation of the EKC, a theory in turn inspired by the primer work of Kuznets.

1.2.1 The Forest Development Path

According to Hyde (2012) "[a] common pattern of forest development emerges from observations take almost anywhere the world and from almost any period in time"

[17] Actually, the FDP could be placed between the EKC and the FT since it embodies elements from both of them. It could be argued that time and GDP—x-axis of FT and EKC, respectively—are considered together along the economic evolution of countries in three different stages. As concern y-axis, both forest cover and deforestation rates concur to determine forestland values.

[p.15] and his model represent the attempt to give a common analytical face to this pattern. Although the model is built on assumptions and hypothesis—as well as any economic model—it is not the reflection of a true reality nor a particular country context but a more general environment which try to incorporate all of these elements: economic geography or location, natural and managed forest, transaction costs, and dynamic change in the forest properties.[18]

The model[19] begins with a classic von Thünen's homogeneous plain environment with an unsettled frontier of forest and grassland. Here farmers and miners are the first settlers which move along the frontier by converting those lands into agriculture and pasture. A graphical transposition of the model should be interpreted in the following way: the horizontal axis represents the distance from the market (the origin) and moving forward to the right the environment shift from agriculture to forest; the vertical axis instead represents the value of the land rent regardless of whether it is agriculture or forest land. Depending on respective value functions, agriculture and forest compete as shown in Figure 1.2 which represents the model first proposed in Hyde *et al.* (1996). The value of agricultural land for each settlement, described by the function V_a, is a decreasing function of the distance from the market[20] and reaches its zero value at point C after which the cost to convert and sustain an agricultural land exceeds any potential return. Conversely, V_f is the natural forest declining functions which reflects the net discounted value for the standing forest resources, from timber to other wood and non-wood products. This function has a lower slope compared to the one of agricultural land since the value of standing forest resources[21] is lower than agricultural land use.[22] The point h is where the value of the land is equal both in terms of agriculture and forest. In

[18]The model here presented is retrieved from Chapter 2 of the book *The Global Economics of Forestry* (Hyde, 2012) and its introduction from the work of Hyde *et al.* (1996).

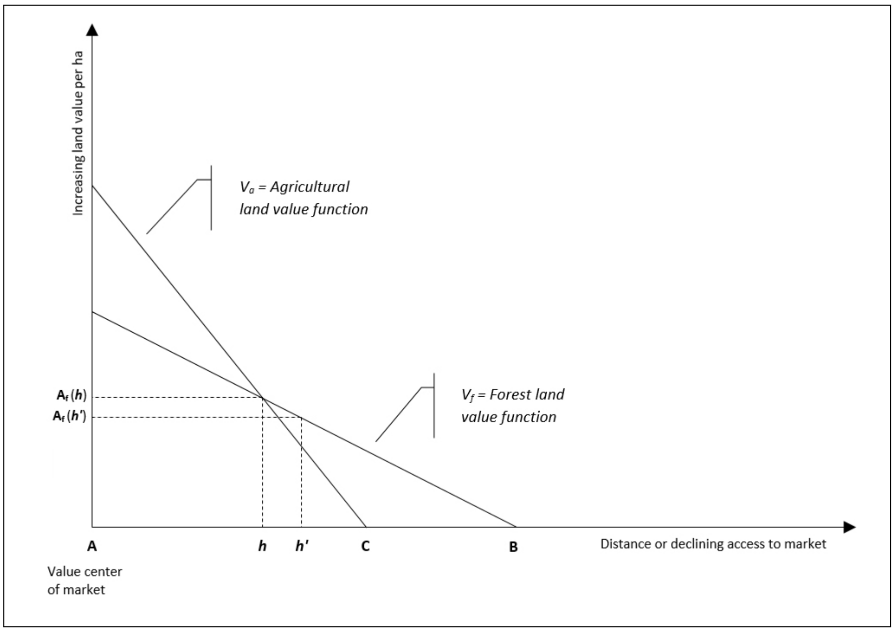
[19]A similar presentation could be found in the work of Louman *et al.* (2011).

[20]More specifically, V_a is a function of the net farmgate price of agricultural products which is greatest the more the settlement is close to the market due to minimal transportation costs. The vertical distance between any point on V_a and the corresponding level and typology of land on the horizontal axis represents the economic rent for the unit of bare land at that point. For example, "$V_a(h)$ is the sum of discounted net expected returns to this unit of land obtained over time by the agent that manages it" or even "the discounted sum of periodic returns from market revenues and household subsistence values minus the discounted sum of production costs incurred to obtain these returns" (Hyde, 2012)[p.17].

[21]Similar to agricultural land, $V_f(h')$ represents the net return from an undeveloped forest land. Even in this case is possible to identify this amount as the discounted net expected returns from selling forest and non forest products from this unit of land minus the burden sustained to harvest, produce, and sell them.

[22]Notice that the value of agriculture would have always a greater value compared to forest since products from this land are necessary for human subsistence. It could be argued that even forests are

Figure 1.2 *The relationship between land value and market access*



Source: Author's personal elaboration based on Hyde *et al.* (1996) and Hyde (2012).

other words, revenues obtained from converting the forest land into agricultural land and selling product to the market is equal to harvest the land and sell forest products to the market. After this point, economic forestry activities become those preferred and the difference between V_f and V_a represents the higher profitability of forestry over agriculture. Later, forestry remains economically viable until its value declines to zero in B. Nonetheless, between h and B it must be considered even the role of property rights (function not showed in Figure 1.2) and the cost of securing them for both agricultural and management forests. In fact, between this range the cost of establishing and protecting the rights over some land (activities) became higher than the *in situ* value of the land. After this threshold, forestland becomes an open-access resource.[23] However, Figure 1.2 could represent a mature state of forest development, thus it is necessary a step back to retrace the whole path.

A new forest frontier, stage I

The first stage of the forest development path starts from a new unsettled frontier where farmers or miners convert forestland into new activities as showed in Figure

able to provide basic human subsistence for survival (for example, untouched indigenous tribes in the Amazon) but it would be a case outside a market economy context.

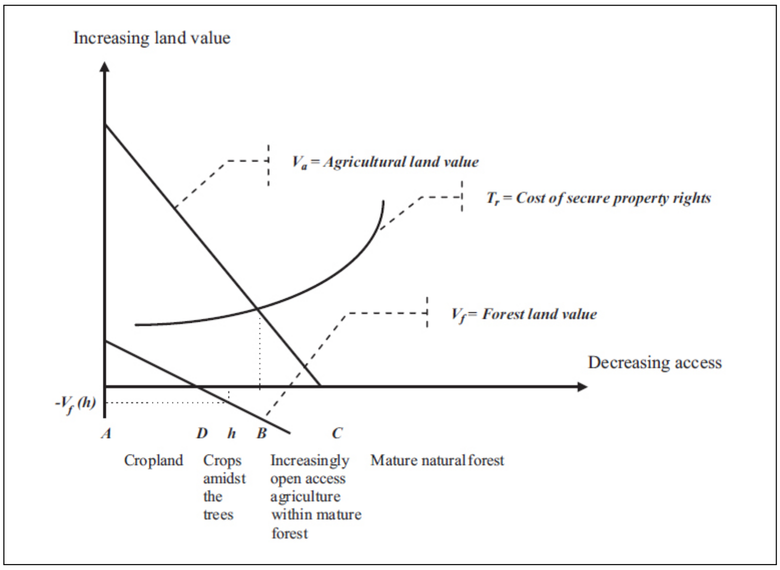
[23]The forest value function "reflects only short-run or extractive resource values. Generally, the costs of establishing and protecting permanent rights to the land are greater than the value of the land for long-run forest production for all land beyond point [h]" Hyde *et al.* (1996)[p.226].

1.3 which is similar to the previous Figure 1.2 but differs by two main elements. First, a low function of forest land value since countries lie into a first phase of development characterized by a primary role of agriculture and a pre-industrial environment which implies low prices for forest products. Second, the presence of the curve T_r which represents the cost of secure property rights—also called transaction costs—that increases as the level of infrastructures and effective control declines as the distance from the market center A increases. The intersection between V_a and T_r falls in point B, thus new farmers manage the area AB while BC is used only to gather products for short-term advantages, without a continued use. Therefore, since the cost to secure these lands is higher than the expected agricultural or forest returns, these forests becomes essentially an open-access land.

Concerning trees in this area which interfere with agriculture—in particular the segment DB—, they are removed if the expected return on the converted land plus the gains for selling trees or use them for construction or fuelwood purposes exceed removal and delivery costs. However, in this first stage of development the curve V_f is always below V_a and the fact that $V_f(h)$ could be negative, represents the burden to have trees which interfere with agricultural activities. Furthermore, the only costs associated with forest are those of harvest and delivery since farmers have do deal with a mature untouched forest where forest management activities, and relative costs, are absent. Accordingly, if the market price for forest products just equals harvest and delivery costs, the value of forests at the harvest point D is equal to zero.

In this first stage, two characterizations of agriculture are contemplated: shifting cultivation and permanent settlement. Shifting cultivation is a subsistence practice of farming where an unit of land is farmed until the point when soil nutrients are depleted, then farmers move forward to clear a new forest area for their needs. This behavior tends to decrease the plot of land's value with a downward shift of the function V_a. Farmers move to forest land close to their previous homestead moving away from the market center. Consequently, the more farmers move into forest, the more the act of obtaining forest products became costly and valuable eliciting an upward shift of the forest value function V_f. Shifting cultivation will continue as long as quality forests (to be converted into agricultural land) are available, or the population growth, labor opportunity cost decline, and the quality of available land declines as well at the point where is more valuable to invest in previous farmlands. After the phenomena of shifting cultivation, when more advanced practices of management are adopted, households became stationary creating permanent

Figure 1.3 *A new forest frontier, stage I*



Source: Hyde (2012)[p.16].

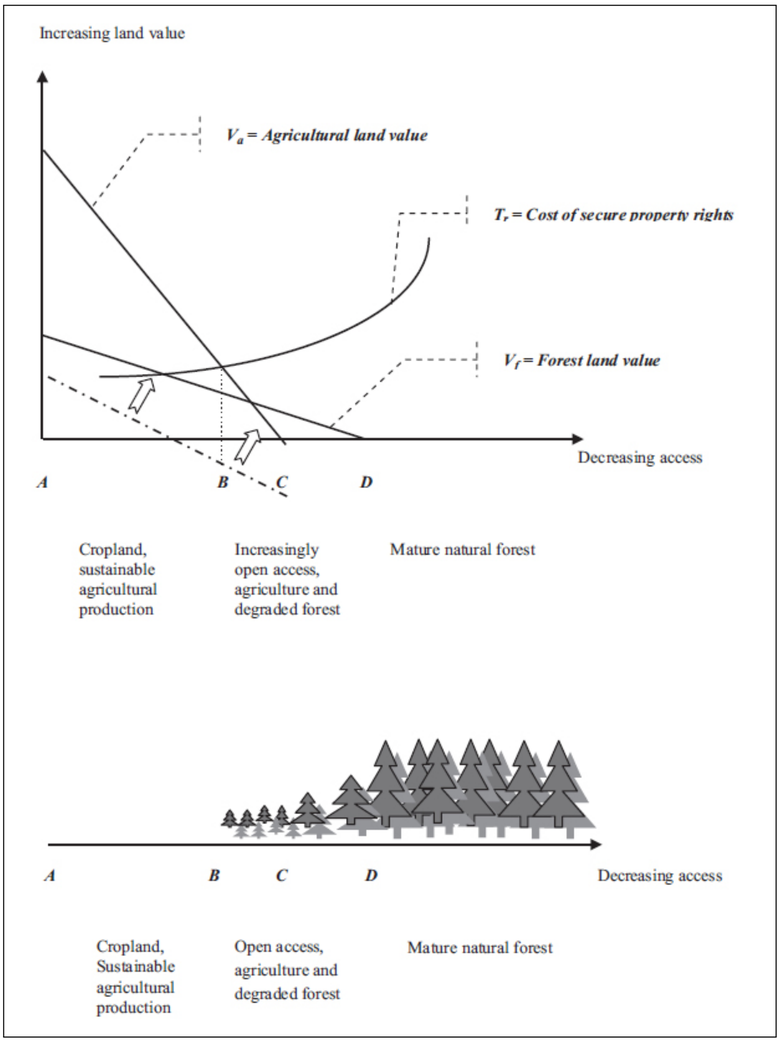
settlements. At this point, the forest frontier D has shifted to the right since forest products now are more distant from the market and their values must necessarily rise since harvesting and delivery process require more efforts to be performed.

A developing forest frontier, stage II

The growing demand for agricultural land, construction timber, and fuelwood represents the justification for the removal of natural forest at the margin of sustainable agriculture at point B. However, if the demand for forest products remains high and well sustained, the removal of natural forest will continue and then the value gradient of the forest land will rise upward as illustrated in Figure 1.4. The important distinction between this second phase and the previous one is that now deforestation is mainly spurred by commercial forest activities such as logging and not, similarly to the previous phase, by agricultural land conversion. Furthermore, the open access area, determined by the curve T_r, now it is only partially devoted to agriculture (BC) and most governments tend to protect lands over B and also over D by absorbing the increasing cost to secure lands. Unfortunately, illegal logging and open access exploitation is now a common phenomena as well.

In this phase the area of open access forest requires some attention. In fact, in this area forests will not be fully deforested but selectively harvested and degraded until the expected return of the low-level forest products is less than the opportunity cost of the labor and the capital necessary for the extraction of these products. The

Figure 1.4 *A developing forest frontier, stage II*



Source: Hyde (2012)[p.21].

image ad the bottom of Figure 1.4 gives the idea of the forest density in the area *BD*.[24] However, the point *D* could further penetrate in the area of natural forest generating a higher area of degraded forests. For example, two equal regions in the second phase which differ only in terms of opportunity cost of extractions will have two different areas of degraded open-access forest. The difference would be in a more flatter function of forest value for the region with lower extraction costs (or

[24]In some cases it is possible to observe a remarkable difference between the volume and species in the remaining area *BC* and those after point *D*. For example, temperate forests are characterized by few species which tend to be selectively harvested with large shares or completely, thus the evidence of a hypothetical boundary in *D* could be elevated. Conversely, tropical forests, characterized by higher biodiversity and species, present great amounts of low-profitable products and the harvesting process is more selective on high-value species (*e.g.* ebony trees), thus the degradation is potentially less pronounced or rather evident.

lower opportunity costs) which intersects the horizontal axis in point D further in the area of natural forest. The other region, with higher extraction costs (or higher opportunity costs) would have a relative steeper function—for example similar to the one in Figure 1.4—with a smaller area of degraded open access forest and more untouched natural forests.[25] Eventually, open access areas are a primary source of illegal logging, one of the most important problems related to international timber trade which affects both developing and developed countries. This occurs when the log value is positive but the enforcement cost to protect the forest at risk is too elevated.

Natural forest exploitation represents the main driver during the entire second phase. Deforestation continues and the forest margin D slowly shifts more and more inside the untouched natural forest moving farther from the market center. This raises the prices of forest products but not to a sufficient level able to incentive any process of tree planting or forest management activities since the function V_f is still located under the curve T_r when the shift between V_a and V_f occurs in their intersection.

A mature forest frontier, stage III

The continued use of forest products and the general economic development of the country will sustain the growth of the forest value function V_f which continues to move upward with a consequent shift on the right of the frontier of economic activity. However, this constant moving away of the point D from the market center will rise delivery costs and local prices of forest products to a level such that to induce a substitution in these materials. This substitution for example could take the form of different construction material, such as brick and stone or fuelwood alternatives. Furthermore, the industrial evolution of these countries could generate even better and economically favorable alternatives. This substitution could take place in the form of different forest products. In fact, the elevated value of forest products now could justify activities of permanent forest management in the previous degraded land with property rights. Products from management forests

[25] Hyde (2012) mentions the examples of rural areas of the arid southeastern India to identify the first region with low opportunity costs and the rural southwestern Virginia in the United States to identify the second region with higher opportunity costs, instead. The first case is characterized by an area where population is poor and labor opportunities are limited and the vegetation after the agricultural extension is beyond degradation. Conversely, in the second case, forest' degradation is not noticeable since some itinerant families collect forest sub-products to sale them as Christmas greenery. In this case, albeit the poverty of these families, their labor opportunities are higher than those in southeastern India.

then become the alternative to products harvested and delivered from open access natural forests. This new area of managed forest could take the form of forest plantations, agroforestry, but also trees in private gardens, roadsides, and parks.[26]

Figure 1.5 shows the final stage of the FDP where the forest frontier could be defined mature. Now the interception between V_a and T_r occurs under the curve of forest value, then sustainable forest activities are economically possible along the segment $B'B''$. Frontiers still remain since some removals on natural stocks along the open access forest area CD are competitive with sustainable forest activities. In fact, marginal cost of harvesting in this area and then delivery to the market is equal to the marginal cost of growing, harvesting, and delivering products from managed forest to the market.[27] Using a Ricardian approach,[28] it could be said that forests are characterized by three different margins: intensive margin,[29] the interception between V_a and V_f at level B'; extensive margin,[30] the interception between V_f and T_r at level B''; and a third margin, at the frontier in D, an additional margin compared to the classic land-rent theory dichotomy.

This three-stage characterization of the development of forests identify three typologies of forest cover: (1) managed forest, which includes industrial forest, plantations and trees in residential areas and cities, the area $B'B''$; (2) degraded natural forest, from point B up to D; (3) unmarketable mature natural forest located after point D. However, a more precise distinction of this last point would identify first a neighbor area of unsustainable harvest activity, just after D and then the continuum of mature natural forest without market value.

The bottom image in Figure 1.5 shows how alongside a degraded natural forest, there is also the growing stock of the sustainable forest plantations.[31] Therefore, this means that the total forest area of a country could eventually recover from the

[26]These last three categories are generally not accounted in national inventories but their relevance is undeniable (FAO, 2001b).

[27]Removals in the natural forest zone could be costly due to marginal delivery cost that are greater the more the harvesting process distances from the market and higher marginal harvesting costs due to the non homogeneity of natural forests if compared to managed forests. However, the marginal growing costs which characterize this latter category could offset other lower marginal costs and this could eventually justify the competitiveness between these two sources of forest products.

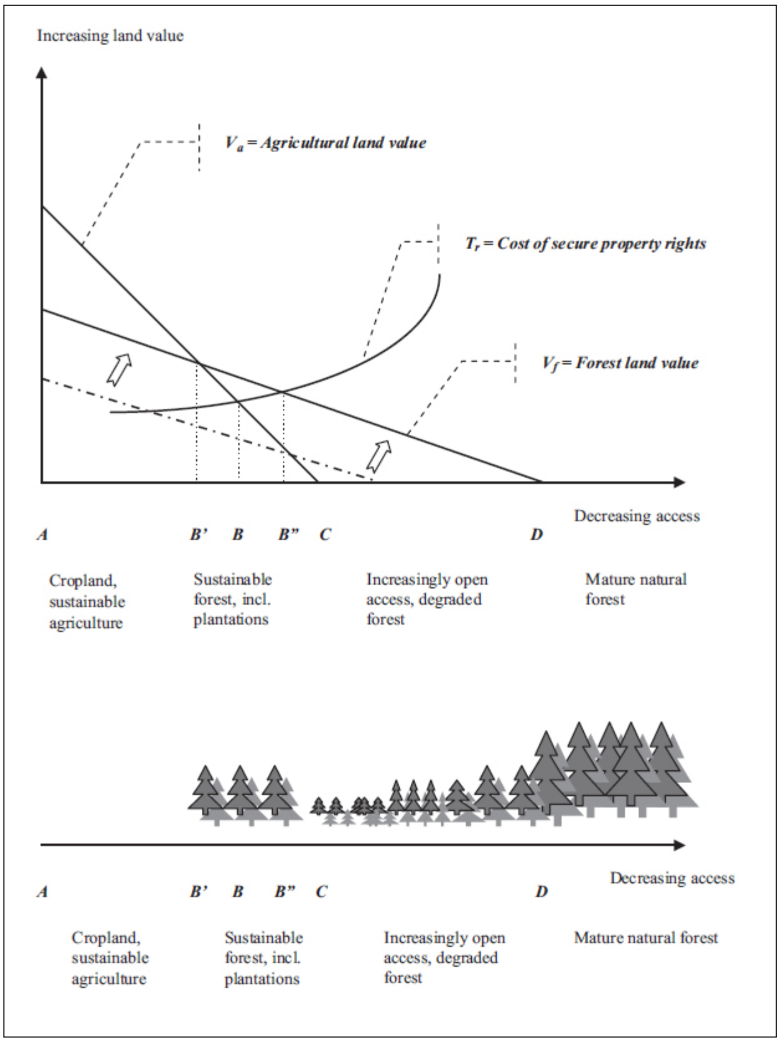
[28]A review of the Ricardian rent theory could be found in the work of Bidard *et al.* (2014).

[29]Here is where intensive cultivations occur under a typical land-rent theory, thus increases in agricultural production occurs only by applying more units of labor and capital.

[30]Conversely, here is where cultivations are characterized by an extension of the farmed area in order to increase agricultural production.

[31]In the proposition of Louman *et al.* (2011), in addition to the gross rent for agriculture (GRA) curve (which is substantially equivalent to V_a in Hyde's proposition), two curves of forest rents (or V_f) could be found: gross rent of open access forest use (GRF) and gross rent of responsible management forest (GRRFM). These two curves embody the competition between open access and management

Figure 1.5 *A mature forest frontier, stage III*



Source: Hyde (2012)[p.31].

previous stage, characterized by an increasing degraded open access fores land. In the first two stages harvest always exceed growth while in the third phase the equilibrium is more delicate but at the beginning still in favor of an exceed of harvest over growth. In fact, the combination of harvest on management and natural forest exceed natural growth rates even in this third phase. Nonetheless, when forest volumes of these countries begin to include even forest for shade, parks, erosion control, non-extractive use, and abandoned agricultural land begin to revert to forests, then the volume of growth could be large enough to offset harvest rates.[32]

forests: if the rents from management forests net of transaction costs (or T_r) are greater than rents from open access forest, the first use of land would be preferred.

[32]This list contains several non-market use of forest which can occur in this third phase, in conjunction with growing level of economic development. In fact, people now could want to

Here lies the possible turning point of the EKC and then the connection between these two theories since when the level of forest growth will overtake the harvesting level, it will occur in conjunction with certain economic development of the country.

1.3 The Environmental Kuznets Curve

The famous EKC finds his inspiration in the work of Kuznets (1955) which first proposed the fascinating hypothesis that during the economic development path of countries income disparities among individuals first grow and then tend to decrease. Some decades later, Grossman and Krueger (1991) applied this idea to a different relation: environment and economic growth. They investigated economic impacts of the NAFTA and its possible environmental implications for Mexico. In fact, at the beginnings of the nineteen, environmental advocacy groups pointed out several risk related to the implementation of this agreement and in general to an increase in trade liberalization between Mexico and North America. The common belief affiliated economic growth and trade openness to a worsening in environment, especially for weaker countries, in this case Mexico. The authors first distinguished three mechanisms that can affect pollution and depletion of natural resources due to a change in trade and foreign investment policies: scale, composition, and technique effect. Through the *scale effect* liberalization in trade and investment leads to an increase in economic activities, but if the nature of these activities does not improve, the total amount of pollution will increase. Furthermore, the *composition effect* is a result of any change in trade policies. More liberalization drives countries to specialize in sectors where they have a competitive advantage. This advantage could be represented both from a less tighten environmental regulations or a more classic factor abundance and technology. In the first case, countries will specialize in less regulated activities pushing out others. In the second case, liberalization will push countries to specialize in the sector which they use the more abundant factors.[33] The net effect is not necessarily an environmental deterioration since it will depend upon whether pollution-intensive activities expands or not according to regulation and factors. Lastly, *technology effect* means that countries can change their production methodologies through foreign investments and trade meaning that the output of pollution per unit of products does not (necessarily) remain the same.

have not only some growing stocks of forest to sell in the market but even forest for recreational use (from their backyard to national parks and reserves).

[33] This reflects the basic characteristics of the famous Heckscher–Ohlin model of international trade (Feenstra, 2015).

In fact, more advanced countries can transfer their technologies to less developed countries and the general increase of income levels generated by trade liberalization can spur policy makers to demand a cleaner environment.

Grossman and Krueger (1991) investigated the relative magnitudes of scale and technique effects analyzing a cross-country sample of comparable measures of pollution in various urban areas (52 cities in 32 countries). More specifically, using the *Global Environmental Monitoring System* (GEMS)[34] database for the period 1977–1988 they found "that ambient levels of both sulphur dioxide [SO_2] and dark matter suspended in the air [SPM][35] increase with per capita GDP and low levels of national income, but decrease with per capita GDP at higher levels of income" (Grossman and Krueger, 1991)[p.5]. This passage represented the first claims for a possible existence of an EKC even though at that time Kuznets had not (yet) been called into question. Furthermore, the authors found a turning point between US$ 4,000–5,000[36] for these two pollutants while for suspended particles they found a monotonically decreasing relation with GDP.[37] The performed model considered linear, quadratic, and cubic terms of GDP in order to account for EKC's shapes. Their results actually showed a slightly "return" of environmental degradation for high levels of growth giving the idea of an N-shape curve. However, authors explained this upward by the presence of only two countries with high levels of GDP (Canada and United States), thus they suggested to do not take this as a strong evidence.[38] Hereafter, the cubic term of GDP will be often addressed across the literature of EKC. Figure 1.6 reports the evidences founded by Grossman and Krueger (1991) for the three pollutants derived from the estimation of their equations,[39] thus a kind of first graphical representation fo the EKC curve. Eventually, concerning the composition effect, the conclusion excluded a possible environmental downgrade for Mexico. In fact, since this country has comparative advantages in activities considered relatively "cleaner" than the average (agriculture and labor-intensive manufactures),

[34]This database represented a joint effort of the World Health Organisation (WHO) and the United Nations Environmental Program (UNEP).

[35]This is a way to measure suspended particles in the air, the other method measures the total weight of suspended particles.

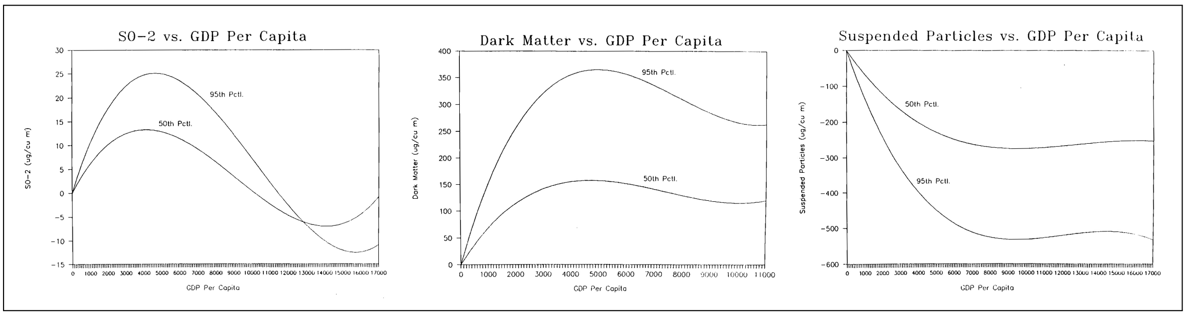
[36]Measured in 1985 US$.

[37]This is the other variables used to measure suspended particles in the air. Since the other one, dark matter, has the EKC shape, it is possible to conclude cautiously that suspended particles has a kind of EKC's shape related to economic growth.

[38]Note that although the aim of the authors was to evaluate possible environmental implication of the NAFTA for Mexico, their evaluations did not include this country due to a lack of data. Thus, their general findings about curves' shapes and turning points have been applied to the Mexican economic situation at that time.

[39]50^{th} and 95^{th} percentile of daily observations.

Figure 1.6 *First representation of the EKC for selected air pollutions*



Source: Grossman and Krueger (1991)[pp.43-45].

trade liberalization could have helped in reducing pollution. Conversely, a slightly increase in environmental degradation had occurred in Canada and United States (specialized in more physical and human-intensive activities). However, the net effect of these interactions conclude for a net benefit for the environment considering also that dissimilarity in regulation would have a minor role in driving inter-sectoral resource allocations among NAFTA countries.

The original name *Environmental Kuznets Curve* was first proposed by Panayotou (1992) and Selden and Song (1994).[40] The basic explication of the EKC could be easily presented through the words of Panayotou (1993)[p.1]:

> At low levels of development both the quantity and intensity of environmental degradation is limited to the impacts of subsistence economic activity on the resource base and to limited quantities of biodegradable wastes. As economic development accelerates with the intensification of agriculture and other resource extraction and the take-off of industrialization, the rates of resource depletion begin to exceed the rates of resource regeneration, and waste generation increases in quantity and toxicity. At higher levels of development, structural change towards information-intensive industries and services coupled with increased environmental awareness, enforcement of environmental regulations, better technology and higher environmental expenditures, result in levelling off and gradual decline of environmental degradation.

Keeping in mind this relatively easy justification of the EKC, the following paragraphs will retrace the first works which have characterized the EKC's literature and the fundamentals of this assumptions. Therefore, the classic model to assess this reverse U-shape relation between growth and environment will be presented alongside other possible paths of the curve and criticisms raised against this hypothesis.

[40] It was still a working paper in 1992.

1.3.1 Main literature on the EKC

The groundbreaking work of Grossman and Krueger (1991) has been followed by several similar works in successive years which substantially confirmed previous findings and enlarged the analysis to other pollutants and natural resources. Among others is it worth mentioning the works of Shafik and Bandyopadhyay (1992),[41] Panayotou (1993), and Selden and Song (1994). However, results differed among these works due to changes in data usage, methodologies, and typologies of environmental degradations investigated.

Shafik and Bandyopadhyay (1992) extended the EKC for ten different indicators of environmental degradation considering not only air pollution but also deforestation, water pollution, municipal waste and sanitation.[42] They considered data for 149 over the period 1960–1990[43] including linear, quadratic, and cubic logarithmic form of GDP tested with panel data techniques (*e.g.* Baltagi, 2013; Hsiao, 2014). They were the first to test the EKC with a notable number of other control variables.[44] Results showed the existence of an EKC not for all the variables. Water pollution, municipal waste and carbon emission increased with GDP while the lack of clean water and sanitation had an opposite tendency. Deforestation resulted to be independent of income levels[45] but air pollution followed the hump-shape form with turning points between US$ 3,000–4,000. Lastly, must be mentioned the fact that carbon monoxide (CO) showed a monotonically increasing relation with income—or turning point levels out of the sample range—due to the fact that this represents a global and not local pollutant. Moreover, a couple of years after this work, Shafik (1994) proposed another similar analysis.

Panayotou (1993) demonstrated the existence of an EKC for deforestation[46] and per capita SO_2 and nitrogen oxides (NO_x) by using cross-section data and Ordinary Least Squares (OLS) techniques (*e.g.* Wooldridge, 2015) without the cubic form of GDP. Concerning the two pollutants, with data from late 1980s of 55 countries, the

[41] This work does not speak in terms of EKC since at the time this terms had not yet been coined.

[42] The complete list of indicators tested is the following: lack of safe water, lack of urban sanitation, annual deforestation, total deforestation, dissolved oxygen in rivers, ambient SPM, ambient SO_2, municipal waste per capita, and carbon emissions per capita.

[43] However, number of countries and year ranges changes slightly among indicators due to data availability.

[44] They tested the following variables for each one of the dependent variables: investments, income growth, electricity tariffs, share of trade in GDP, parallel market premium, dollar's index of openness, debt, political rights, and civil liberties.

[45] This issue is further addressed in Section 1.3.

[46] This issue is further addressed in Section 1.3.

turning point for SO_2 has been estimated around US\$ 3,000–5,000, which is basically in line with Grossman and Krueger (1991) and Shafik and Bandyopadhyay (1992). Conversely, regarding NO_x the turning point resulted to be higher.

Selden and Song (1994) used data retrieved from the World Resources Institute (WRI, 1991) to estimate SO_2, NO_x, SPM, and CO emissions. Since they agglomerated city data for countries and per capita, the results, although characterized by the EKC shape, have turning points far higher than those previous founded by Grossman and Krueger (1991). For SO_2 equals to US\$ 8,700, for NO_x to US\$ 11,200, for SPM to US\$ 10,300, and for CO to US\$ 5,600. These differences with other primer results, could be explained by the use of longitudinal and cross-section data according to Panayotou (2003).

Some years after their pioneering work, Grossman and Krueger (1995) conducted a similar analysis of the EKC increasing the number of variables addressed to fourteen, even this time with GEMS data. Their results confirmed previous findings, but with little evidence that environment deteriorates steadily with growth. Notwithstanding, the main conclusion was again for the existence of the EKC with an average turning point around US\$ 8,000. Concerning SO_2 the estimated turning point was just over US\$ 4,000 while for dark matter higher than US\$ 6,000. Only nitrates and cadmium resulted with peaks greater than US\$ 10,000. Since the model included the cubic form of GDP, for some pollutants higher values of GDP—as for their first study—seemed to be associated with a return in degradation. However, even in this occasion, the N-shape form was attributed to the presence of few countries with high level of GDP which could have twisted the results.

Even Panayotou (1997) came back to test the EKC but this time with GEMS data and the addition of some policy variables as well as an first attempt to decompose the EKC effect. The database consisted of 30 countries over the period 1982–1994 with a specific focus on SO_2 and the peak of the EKC identified around US\$ 6,000.

Following the lead of first studies on EKC, Cole *et al.* (1997) proposed another empirical analysis composed by fifteen environmental indicators retrieved from the OECD's[47] database mostly covering the period 1970–1992 and for different clusters of countries. In addition to SO_2, NO_x, and SPM they considered also chlorofluorocarbons (CFC), methane, and a particular attention on transports, for emissions, traffic volumes, and energy use. Their findings suggested that the EKC exists only for local level pollutions while indicators with a more global influence tend to increase with income or diminish only with high level of GDP. In a previous

[47] Organisation for Economic Co-operation and Development, founded in 1948.

study Holtz-Eakin and Selden (1995) draw to similar conclusions estimating the EKC for CO_2. Their panel data study focused on 130 countries, from 1951 to 1986 using data of the Oak Ridge National Laboratory (ORNL) (Boden *et al.*, 1992). The results showed a decrease in emission only at high levels of GDP (US$ 35,000) confirming early findings of Shafik and Bandyopadhyay (1992) and Shafik (1994). Using the words of Panayotou (2003) "[t]his conclusion would lead one to expect that CO_2, the global pollutant *par excellence*, would increase monotonically with income, at least within any observable income range since the impacts of global warming are (totally) externalized to other countries and future generations" [p.51].

In 1998 a special issue of the journal Ecological Economics has been dedicated to the EKC considering its high relevance in the environmental economics literature. The work of Torras and Boyce (1998) has been included in this issue and its remarkable peculiarity is the fact that they mentioned a so-called "unsung hypothesis" of Kuznets (1963)[48] and following this lead they conducted an analysis of the EKC for seven environmental variables including right-hand variables able to catch inequality among states.[49] Their results were substantially in line with those of previous studies although the presence of inequality variables in some cases leads to non statistically significant income variables. For example, with smoke there is no turning point since income is not relevant while the peak is equal to US$ 4,350 with the model without inequality variables. Conversely, as concern SO_2 the peak with the basic model is higher compared with the inequality model, from US$ 3,890 to US$ 3,360. Therefore, this result could be seen as an example of how could be flatten the EKC. They concluded for the importance of more equitable societies, especially in developing countries in order to reduce environmental degradation. Moreover, in the same year of Torras and Boyce (1998), Kaufmann *et al.* (1998) founded another peak for SO_2 emissions equal to US$ 14,730. They used data retrieved from the 1993 statistical yearbook of United Nations (UN) covering the period 1974–89 for 23 countries estimated through panel data and with the peculiarity to consider not only GDP per capita but also per area.[50]

After the first round of EKC works, better data started to become available and the attention started to focus more on pollutants with a broad influence, first of all CO_2, following the increasing debate around the matter of global warming after the

[48] In fact, he suggested that power inequality is a function of both income inequality and per capita income.

[49] Among other variables, they considered the GINI ratio, literacy, and political rights.

[50] They divided total GDP by national area to get a proxy of the geographical economic activity.

adoption of the Kyoto Protocol in 1997.[51] With the International Energy Agency IEA (1991) database Galeotti and Lanza (1999) conducted an analysis for CO_2 emissions over the period 1971–1996 for 110 countries.[52] Those have been divided in two groups according to their commitment within the Tokyo Protocol: Annex I for countries who have agreed to reduce GHG emissions below their individual base year level and non-Annex I for countries without obligations from an emission cap (UN, 1992). Their turning points varied between US$ 15,000 and 22,000.[53] Albeit results confirmed the EKC shape, the authors concluded for GHG emissions which will eventually rise in the future due to the growth of economies in the non-Annex I group. In fact, since emissions data is accounted per capita, although these countries could have low levels of emissions per person, their elevated and increasing population will led to an increase in CO_2 emissions in the future. A conclusion which confirmed the previous work of Holtz-Eakin and Selden (1995) without forgetting the fact that first EKC works estimated a monotonic increasing curve for this pollutant with respect to income.

Finally, the EKC could be seen as a seed, planted at the beginning of the nineties, from which have branched over the time a boundless number of tests, applications, models, and critiques. It is for sure a hard task trying to orientate in this "jungle" of literature. Fortunately, there is a discrete amount of surveys about the argument. For the first decade of EKC it is possible to consult the works of Borghesi (1999) and Panayotou (2003) while a recent review is provided by Ginevicius *et al.* (2017). Moreover, a specific focus on results and turning points is provided by some meta-analysis (Stanley *et al.*, 2008) over the EKC (*e.g.* Cavlovic *et al.*, 2000; Goldman, 2012; Jordan, 2010).

1.3.2 Core elements of the EKC

The relation between economic growth and environment expressed with the EKC is considered like a "black box" able to catch only net effect between these two variables. Different aspects are at stake and each one with a different influence. Panayotou (1997), identified three different structural forces.

[51] The Kyoto Protocol is an international treaty which commits State Parties of the UNFCC to reduce GHG emissions. This treaty entered into force in 2005 and the first commitment period expired in 2012 while the second one extends up to 2020 (UN, 1992).

[52] Representing 88% of CO_2 emissions in 1996.

[53] More precisely, the authors used Gamma and Weibull functions (Greene, 2000) to estimate their model for all countries and the two Annex I and non-Annex I groups. The lower peak is equal to US$ 15,073 (the Weibull function for all countries), while the higher peak is equal to US$ 21,757 (the Gamma function for non-Annex I countries).

1. First, the scale of economic activity, or rather the *scale effect* first expressed by Grossman and Krueger (1991), characterized by a monotonic increasing relation between income and pollution.
2. Second, the *composition effect* or structure of economic activity, which represents the shift from high to lower pollution activities expressed by a non monotonic inverted U-shape curve. While the scale effect increases production and pollution at the same time, the economy structure of a country evolves itself from the primary agroprocessing sectors to more industrialized and capital-intensive activities such as chemical and heavy industries with high pollution process. In later stages of development, the presence of information technologies and services rise replacing previous sectors and their less environmental impact contributes in reducing pollution and natural resource depletion along the path of economic growth. However, the same industrial structure does not mean same levels of emissions because technologies among states are of different quality and vintage. The technological level is influenced by relative prices and by the policy and regulatory framework which could be enhanced by trade openness (Panayotou, 1993).
3. Third, *abatement efforts*, or rather the demand and supply of environmental protection and reduction of pollution. From the demand side, low incomes have no effect on the demand for environmental protection since individuals' choices are directed to food and shelter. Conversely, when incomes rise and subsistence needs are more than overcome, the demand shifts to more normal and then superior goods, such as environment and natural resources. From the supply side, higher incomes increase both public and private resources to invest into environment's protection.[54] This aspect is expressed in terms of a positive income-elasticity of environmental goods and protection to income: the more the income growth, the more the demand (and the supply) for these

[54]In early stages of a country's development, tax collection are ineffective and demand for environmental protection low or absent. With the increase of GDP will become gradually feasible to collect taxation to invest in environmental protection and the demand for a healthier environment—which is an income elastic commodity—will rise. At this level individuals will start to demand the implementation of more environmental-oriented policies and also their choices as consumers will be guided by a similar orientation (Panayotou, 1993).

goods grows.[55] Therefore, the curve which link pollution to income for the abatement effect is monotonically decreasing.

For example, Carson *et al.* (1997) demonstrated the positive relationship between income and reduction in pollution for US States while Johansson and Kriström (2007) provided a simple neoclassical micro-foundation model for the existence of an EKC following the first proposition of Stokey (1998).[56] Other models which aim to give a micro-foundation for the EKC are for example those of Munasinghe (1999), Andreoni and Levinson (2001), and Hartman and Kwon (2005) as long as overlapping generation models such as John and Pecchenino (1994) and Jones and Manuelli (1995).

[55]Shafik and Bandyopadhyay (1992) first addressed the matter of income elasticities to environmental goods. In fact, since natural resources are both consumption good and production input, during the development path of a country they will be used according to their income elasticity of demand and supply and they modify with changes in associated costs and benefits deriving from changes in environmental quality or natural resources availability. However, the authors raised some correct observations about these relations.

The marginal cost (MC) of a cleaner environment is defined as an increasing function of environmental quality (E) and the marginal benefit (MB) is a function of both the level of environmental quality and GDP per capita (Y):

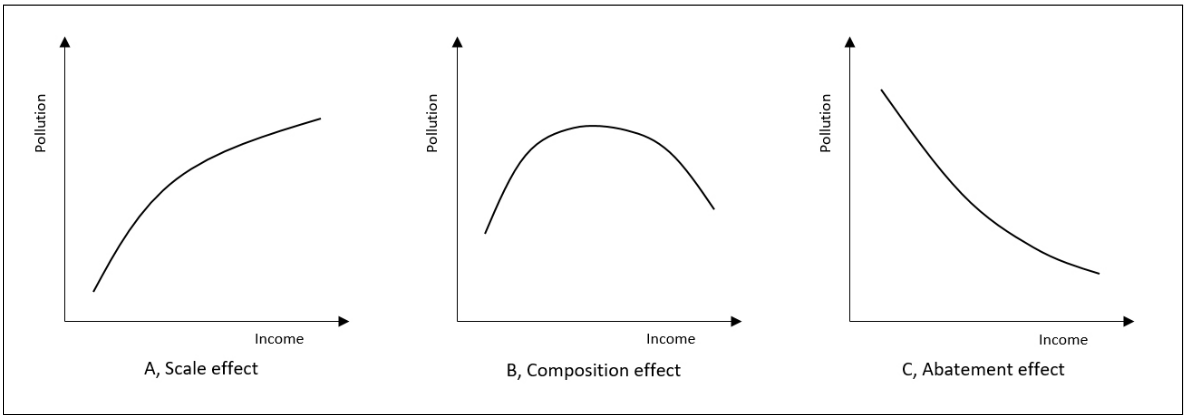
$$MC = f(E) \qquad \text{where} \qquad \frac{dMC}{dE} > 0 \tag{1.1}$$

$$MB = f(E,Y) \qquad \text{where} \qquad \frac{dMC}{dE} > 0 \quad \text{and} \quad \frac{dMB}{dY} > 0 \quad \text{or} \quad < 0 \tag{1.2}$$

While the sign of (MC) is easily defined due to a positive elasticity of costs to environmental quality, it is not possible to define the elasticity of benefits with respect to income since various aspects are involved. In fact, environmental degradation depends of which outputs are produced and those change with income. The view that higher incomes are associates with more health damage due to environmental degradation would increase (MB) when (Y) rises. In other cases, for example when survival thresholds are at stake, the willingness to pay become almost infinity and private benefits to avoiding the damage are elevated. The opposite happens when pollution costs can be externalized. Another questionable matter refers to the tendency to associate more value to the environment—thus require more protection—with higher incomes, but some rural or indigenous societies give high values to the environmental as well. These aspects help to explicate why it is not easy to define the relation between environmental quality and income properly. Eventually, according to Shafik and Bandyopadhyay (1992): "[w]here environmental quality directly affects human welfare, higher incomes tend to be associated with less degradation. But where the costs of environmental damage can be externalized, economic growth results in a steady deterioration of environmental quality" [p.4].

[56]These models are characterized by an exogenous key-role of technology in sustaining economic growth—typical of Solowian models of growth (Solow, 1956). The application of the Solow's growth model has given birth to the so-called Green Solow Model by Brock and Taylor (2010). However, Solowian models in economic literature experienced various evolutions and criticisms. The reassessment of Cesaratto (2010) recounts the evolutions of these models enlightening even the specular overspread of different heterodox theories of growth.

Figure 1.7 *Decomposition of income effects on the environment*



Source: Personal elaboration based on Panayotou (2003).

Figure 1.7 presents the curve for the three income effects on the environment proposed by Panayotou (1997).[57]

(Panayotou, 1993) concludes that "[s]ince the size of the economy, the change in economic and industrial structure, the vintage of technology, the demand for environmental amenities and the level of environmental expenditures are all a function of the level of development, it is reasonable to hypothesize a relationship between environmental degradation [...] and GNP per capita. Furthermore, given the dynamics of structural change, technological development and consumption expenditure explained above, it is reasonable to hypothesize that this relationship is non-linear and has an inverted U-shape" [p.5]. The examples of United States, Western Europe, Japan, South Korea, Taiwan, Hong Kong, and Singapore are presented as countries whose experience conforms to an inverse U-shape relation between environmental quality and economic growth.

This brief overview of the EKC, particularly focused on its very first formulation and results, pointed out various explication for its existence. Eventually, trying to summarize the main elements of the EKC it is possible to identify five factors which can explain the evolution of the curve and its inverted U-shape:

1. *Scale effect*, according to which the more the production increases, the more the environmental pollution rises if production methodologies do not improve, or rather without technological changes. It is possible to assume that a 1% increase in scale production results in a 1% increase in emissions (Stern, 2004).[58] This

[57] Note that each effect is given considering the others as fixed.

[58] However, Andreoni and Levinson (2001) rightly pointed out the possible existence of scale economies or dis-economies of pollutions.

effect could be seen as a monotonic increasing curve of income and pollution as proposed by Panayotou (1997).

2. *Structural changes* or composition effect, which represent the evolution of economy composition of countries, from agriculture and primary production to more pollutant industrial activities in the secondary sector to conclude with services in the tertiary sector. Panayotou (1997) rightly depicted this evolution as a reverse U-shape curve.[59] In this category it is possible to include two elements distinguished by Stern (2004): changes in input and output mix which occur at different levels of development.
3. *International trade*, which allows an increase of changes and production, thus a spur of the scale effect. Countries are able to specialize in the production of goods where they have comparative advantages due to natural resources and different degrees of environmental regulation. International trade could lead to an environmental dumping effect since more developed countries are able to relocate in less developed countries pollutant actives. Conversely, more advanced economies can transfer their less-pollutant technologies to less developed countries. These two effects could be seen as two opposite forces. While the former tend to aggravate the EKC for developing countries, the latter could help to flatten the curve.
4. *Technology effect*, the element which is transversal in both structural changes and international trade. These two previous effects already pointed out the importance of technology as a key role in determining the level of pollution and depletion of natural resources as well as the way to reduce them. Grossman and Krueger (1991) first identified the importance of this effect in determining the EKC albeit they intended it more in terms of trade and increases of income. In this context, according to Stern (2004), improvements in the state of technology lead to changes in productivity, or rather the use of less polluting inputs per unit of output, and emissions specific changes in process, or rather lower emissions per unit of input.
5. *Demand elasticity* or abatement effect, which means that as income increases, individuals will demand for less pollution and for an healthier environment. This aspect could be obviously seen even from the supply side, with the production of more goods with less pollution or depletion of natural resources.

[59] The composition effect as first intended by Grossman and Krueger (1991) was mainly focused on international trade, thus it suits better in the third element of this list.

Furthermore, higher incomes are associated with governments able to implement environmental policies in order to satisfy the demand of citizens made possible by higher revenues. Following Panayotou (1997), this effect could be seen as a monotonic decreasing curve of income and pollution.

Eventually, the EKC could hastily give the idea that environmental degradation represents just a temporary and necessary phenomenon and the economic growth as a panacea. Therefore, policy implications would be centered only on urging a fast economic development in order to reach the turning point and consequently overcome the peak of the curve with no regard for the environment. This could easily turn out to be a wrong solution, as remarked by Panayotou (1993), since ecological thresholds are not taken into account despite they are likely to exists especially for developing countries. Conversely, policies for these countries should be focused on a flattening of the curve in order to prevent environmental irreversibility.

1.3.3 The EKC model

The EKC hypothesis is commonly studied through a cross-country analysis using primarily panel data methodologies as showed in the earliest works of Grossman and Krueger (1991) and Shafik and Bandyopadhyay (1992) but even specific country studies with time series analysis (*e.g.* Hamilton, 1994) and more disaggregated works (*e.g.* regional and municipal levels) could be found in this vast literature. Researchers focus their analysis mainly on air pollution, followed by water pollution and natural resources depletion. The basic model of the EKC is the following:

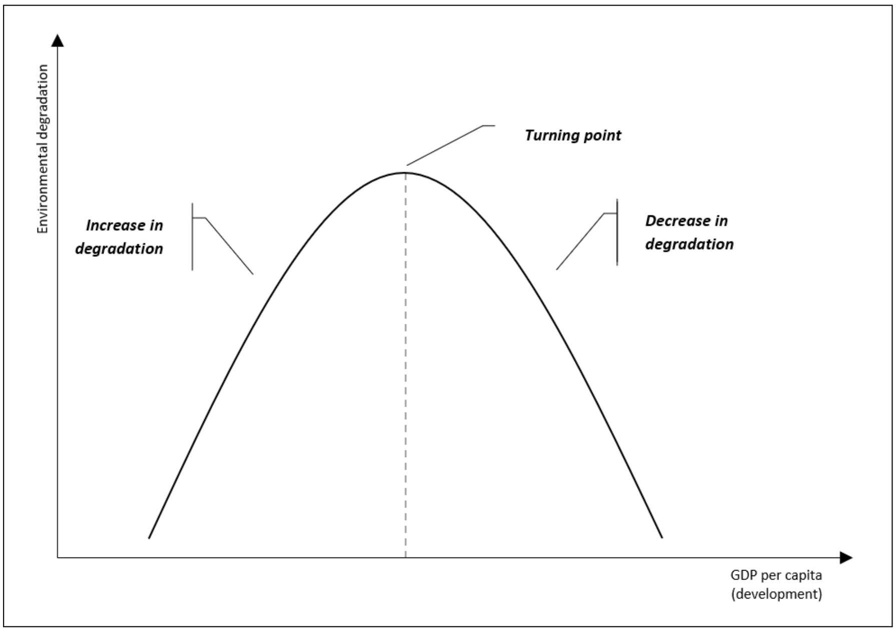
$$POL_{it} = \alpha_i + \lambda_t + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 GDP_{it}^3 + \sum_{j=1}^{k} \beta_j X_{it} + \varepsilon_{it} \tag{1.3}$$

Where POL_{it} represents the environmental degradation or pollution for the country i at time t where $i = 1,2,...,N$ and $t = 1,2,...,T$. α_i is the country's specific effect also called endowments (intercepts in the fixed effects model) and λ_t represents the time effect.[60] Moreover, β_1, β_2, and β_3 are the coefficients for the linear, quadratic, and cubic value of the GDP per capita, respectively.[61] The presence of a cubic element for GDP—even though it could warp the function excessively—aims to evaluate the presence of a possible N-shape curve, thus a return of environmental degradation

[60] The time fixed-effect is not always considered in this literature.

[61] Expressed in constant prices or Purchase Power Parity (PPP). However, in some cases even Gross National Income (GNI) is used in this literature.

Figure 1.8 *The classic representation of the EKC*



Source: Author's personal elaboration.

for high levels of economic growth, or a validation the path of the second half of the curve. X_{it} embodies different right-hand control variables and β_t are they relatives coefficients. Eventually, ε_{it} is the idiosyncratic error of the equation. In order to verify the EKC's hypothesis, the linear GDP term should be positive while the quadratic negative.[62]

According to the different sign of the β coefficients of GDP, it is possible to determine the shape of the EKC. In a survey of the EKC, Dinda (2004) identifies seven possible results:

1. if $\beta_1 = \beta_2 = \beta_3 = 0$ the result is a flat pattern with no relationship between POL and GDP;
2. if $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$ the result is monotonic increasing or a linear relationship between POL and GDP;
3. if $\beta_1 < 0$ and $\beta_2 = \beta_3 = 0$ the result is monotonic decreasing relationship between POL and GDP;
4. if $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 = 0$ the result is the classic invert U-shape relation of the EKC;
5. if $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 = 0$ the result is an U-shape relation;

[62] If the increase of the left-hand variable means an increment of pollution or an augmented environmental degradation.

6. if $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 > 0$ the result is a cubic polynomial or an N-shape curve;
7. if $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 < 0$ the result is an opposite N-shape curve.

The final goal of the EKC is to determine—if it exists—the GDP level where the exploitation rate of the natural resource is lower than the one of growth (in case of pollution, when it starts to decrease), in other words the turning point of the curve. Deriving the equation 1.3 it is possible to identify (if it exists) the maximum of the EKC function.[63]

Figure 1.8 represents the classic graphical version of the EKC where on the x-axis there is GDP per capita, which embodies the economic development, while on the y-axis there is the environmental degradation, commonly quantified in per capita terms too. The first-half of the curve represents the phase where economic growth is associated at first with environmental degradation mainly pulled by industries whose activities generate negative externalities and pressure on natural resources. As the wealth of the country increases and tertiary sectors advance, the economy could reach a break-even point where the growth does not affect negatively the environment anymore, thus the achievement of the turning point.

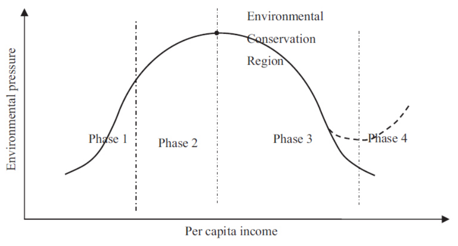
The shape of the EKC presented in figure 1.8 is the "classic" version mainly proposed in this literature (*e.g.* Grossman and Krueger, 1991; Panayotou, 1993; Shafik and Bandyopadhyay, 1992) which follows the equation 1.8 (without considering the cubic term). However, focusing on the left-side of the curve, it assumes high rates of degradation since the very first levels of economic growth of the x-axis. This would be probably unrealistic for the most part of the environmental indicators since with low levels of growth, when states' economies lies of the first stages of the development, with a prominent agricultural and pre-industrial environment, it is reasonable to believe that pollution and environmental degradation would increase with low rates compared to subsequent industrial phases of development. In fact, it must be recalled that any study which aims to assess any possible EKC begins its analysis with already relative high levels of economic growth[64] since country-level data for environmental variables have a restricted time-span coverage.[65] Therefore,

[63]For the basic model, without the cubic term, the maximum value of the function would be equal to $GDP_i = \dfrac{\beta_1}{2\beta_2}$ assuming β_1 to be negative and β_2 positive.

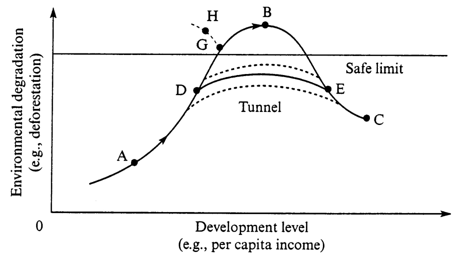
[64]Nonetheless, it is possible to retrieve very long country-level data related to GDP and population. For example, the *Maddison project* provides data over the period 1-2010 AD (Bolt and Zanden, 2014).

[65]For example, data for CO_2 emissions are commonly provided by the Carbon Dioxide Analysis Center CDIAC (2000) and the maximum time coverage is 1751–2015. Furthermore, macro data used

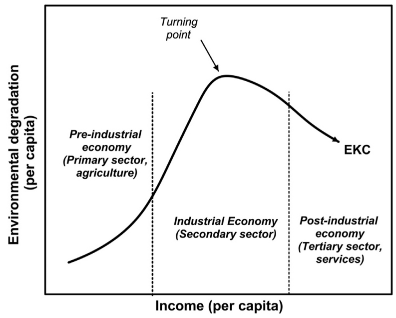
Figure 1.9 *A different shape of the EKC, examples from the literature*



(a) Source: de Bruyn and Heintz (1999)[p.658].



(b) Source: Munasinghe (1999)[p.95].



(c) Source: Kaika and Zervas (2013)[p.1394].

also another representation of the EKC is presented in literature, characterized by a more "realistic" shape of the curve (*e.g.* de Bruyn and Heintz, 1999; Munasinghe, 1999; Kaika and Zervas, 2013) as showed in Figure 1.9. With respect to the canonic version of the EKC (in Figure 1.8), the first half (before the inflection point) is not analyzed despite the fact that its existence is theoretically (and historically) allegedly true.[66]

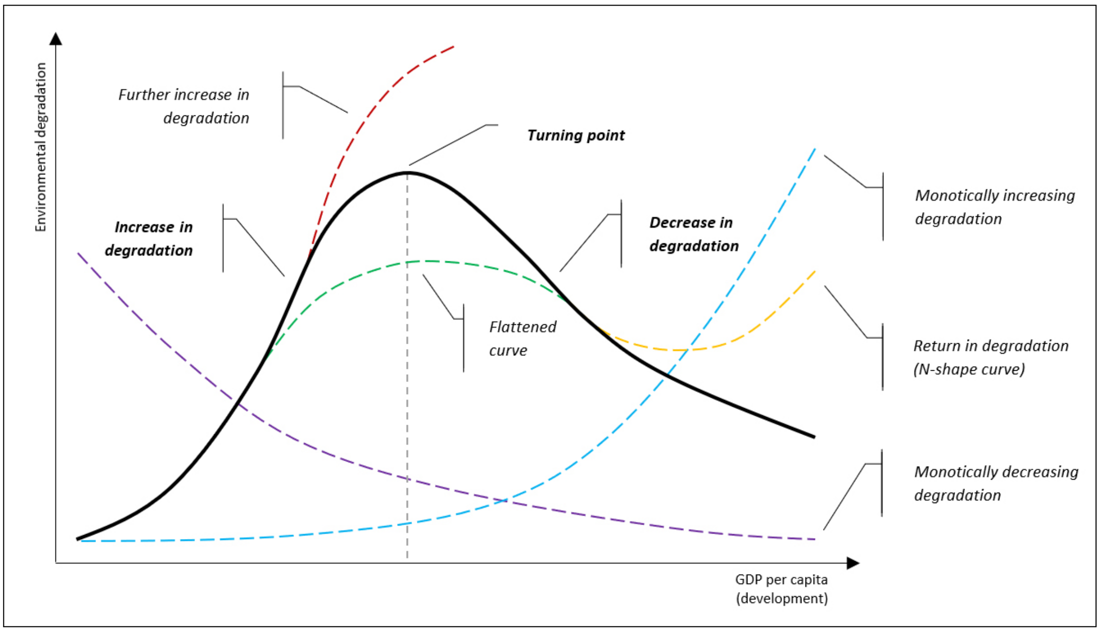
As showed by Dinda (2004), the relation between environmental degradation and economic growth could have different shapes according to coefficients' values. Therefore, Figure 1.10, following the more realistic shape of the EKC, summarizes, with different colored dash-lines various possible paths of this relation.

Since the first proposition of Grossman and Krueger (1991), the cubic term of GDP has been added in the EKC formulation (1.3) and if this terms has the same sign of the linear one, this represents the case of the N-shape curve (the yellow line), a return in environmental degradation with high income levels. Although these results are often justified by the fact that only few observations—richest

for these studies: *Penn World Table 9.0* of Feenstra and Timmer (2015) and *World Development Indicators* of WB (2017), has a similar time span (1950–2015 and 1960–2016, respectively).

[66]Hypothetically, in order to transport into a function this "complete" EKC curve, even a quadruple term of GDP should be added in the Equation 1.3 but the result would be impractical.

Figure 1.10 *The EKC and its possible different paths*



Source: Author's personal elaboration.

countries—are available to high incomes and this skewed the results, this return of an environmental degradation could have some empirical evidence. For example in the Brazilian Amazon, some areas showed the presence of an N-shape relation between GDP and deforestation (Oliveira and Almeida, 2010).[67]

The red line represents the case when the pollution or the depletion of natural resources reached the irreversibility point. Possible further paths of the curve once reached this non-returning point are somewhat uncertain. After the non reversibility point degradation or pollution could increase with higher rates, thus the curve could become steeper. Otherwise, for example in the presence of natural resource, it they have been utterly depleted, the curve, reaching its ceiling, could simply continue with a flat trend. However, it is reasonable to consider another possibility: a backward bending of the curve, where the over pollution or depletion could affect the economic growth of a country eliciting a reduction in incomes thus a worsening of the country's wellbeing as suggested by Munasinghe (1999). These possible paths of the EKC could be explained with the cases of the so-called resource curse or boom-and-bust hypothesis. The former, also known as Dutch disease[68] relies on the first proposition of Prebisch (1962) who stated that countries with rich natural

[67]See Section 1.3.3 for further details.

[68]Terms coined by The Economist (1977) to describe the downfall of Dutch manufacturing sector after the discovery of an huge natural gas field in 1959.

resources experience a slower economic growth compared with countries with less resources. This theory has been further developed by Sachs and Warner (2001) and it is highly debated among development economists. The review of literature carried out by Bulte *et al.* (2005) tested also a possible existence of this hypothesis for 97 countries concluding that, despite the complexity relation between use of resources and development, countries with more resources result to have less level of growth. However, the main reason for this behavior is attributed to a lack of good institutions. The second hypothesis, boom-and-bust, is mainly applied to the forest case, where the presence of valuable forests could spur an initial "boom" of growth and forest production but if it is not accompanied by investment opportunities, the results would be a successive period of long "bust". In describing this phenomena Hyde (2012) mentions the cases of British Columbia in Canada and Washington in United States. This hypothesis has been also used also to describe deforestation in the Brazilian Amazon despite being criticized later (*e.g.* Weinhold *et al.*, 2015).[69]

The monotonic decreasing purple line is commonly associated to some lack of goods and services, such as urban sanitation and safe water. Elements which rise with income growth and decrease of rural population in favor of urbanization (*e.g.* Shafik, 1994; Shafik and Bandyopadhyay, 1992). However, with a more disaggregated analysis Carson *et al.* (1997) evidenced this path even for SO_2, NO_x, and SPM for US States.

Conversely, the monotonic increasing blue line fits with wide dispersed pollutants, such as CO_2, which tend to increase with economic growth since they are commensurate with population and a decrease arrives only at high levels of income (*e.g.* Shafik and Bandyopadhyay, 1992; Shafik, 1994; Holtz-Eakin and Selden, 1995; Cole *et al.*, 1997; Galeotti and Lanza, 1999). This trend, with high turning points is evidenced by Selden and Song (1994) even for SO_2, NO_x, and SPM. Moreover, even municipal solid waste and biochemical oxygen demand rise monastically with income since they are strictly associated with growth and urbanization (e.g Cole *et al.*, 1997; Shafik, 1994). However, some other possible shapes[70] of the EKC could be found in the literature and the survey of Panayotou (2003) gives a graphical intuition of possible EKCs.

The EKC with its bell-shape implies "a certain inevitability of environmental degradation along a country's development path, especially during the take off

[69]See Section 1.3.3 for further details.

[70]For example, a study of deforestation for the Brazilian Amazon presented if Section 1.3.3 concludes for an U-shape relation (but not reverse) between forest loss and income growth (Jusys, 2016).

process of industrialization" (Panayotou, 1993)[p.14]. Thus, the best way to grow and preserve the environment—in the future—is to urge the economic growth with policies of liberalization, economic restructuring and price reforms. However, this flippant interpretation of the EKC could lead to non optimal policies. Panayotou (1992) identified four reasons why the implementation of these policies only growth-oriented are unsuitable. First, the positive slope of the curve could require decades in order to be reached, thus the present value of future growth and clean environment could be easily offset by high rates of environmental degradation at the present. Second, the possibility to prevent some environment losses may be less costly today than in the future. Third, for some environmental degradation there is a non-returning point, thus no reversibility in the future and for this reason they need to be handled in advance. Fourth, the fact that some environmental degradation, such as soil erosion or resilience to natural disasters can easily affect the economic growth of a country. Therefore, a blind and hasty policy maker could easily fall in the "red-path" of Figure 1.10, where the level of environmental degradation is too elevated and excessively if not impossible to be reversible likely with negative effects on the economic growth as well. For this reason "environmental degradation may need to be attacked directly through environmental policies and investments in order to remove obstacles to economic growth itself" (Panayotou, 1993)[p.15].

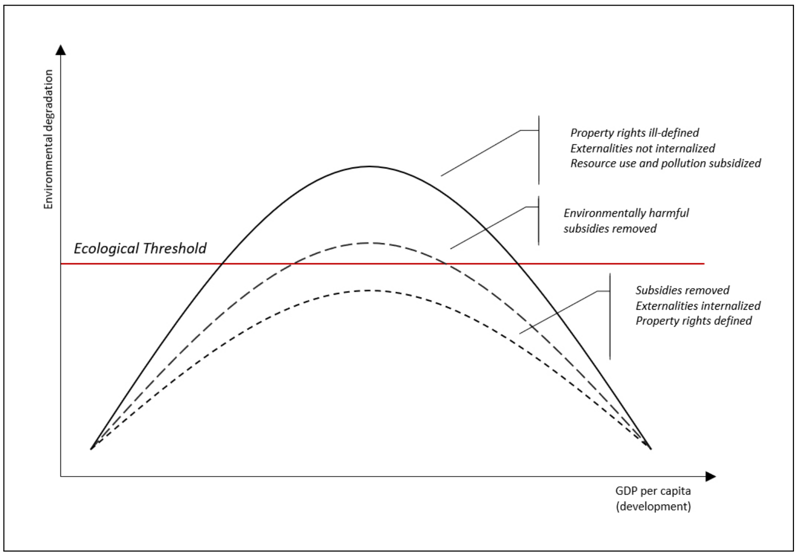
Therefore, knowing the shape and especially the peak of the EKC, the role of policy makers should be the achieving of a flattened curve, the green line of Figure 1.8.[71] Panayotou (1993) identified the sharpest EKC when property rights are ill-define, externalized not internalized, and when pollution and resource use activities are subsidize. The peak of this curve is far more higher than an hypothetical ecological threshold and the removal of subsidized still does not flatten the curve enough to be underneath th un-reversible threshold since even internalization of externalities and definition of property rights are required. A reproposition of the flattened EKC curve advocated by Panayotou (1993) is showed in Figure 1.11.

However, there is no one-size-fit-all reason for this inversion in the EKC since several phenomena could contribute simultaneously. An increased wealth for individuals changes their relation to natural resources and in general to the environment[72] acting and demanding for its protection. Consequently, environmental-oriented public policies could be adopted by policy makers to boost and thus achieve this goal. Technological improvements can shift production—especially agriculture and

[71] This path of the curve could be also called "tunneling" since it could be interpreted as a gallery dug into the EKC mountain.

[72] Now the environment could be considered a luxury good.

Figure 1.11 *Flattening out the EKC*



Source: Author's personal elaboration based on Panayotou (1993).

industry—to less-pollutant processes reducing negative externalities and pressure on natural resources.

At that level international trade could represent a useful tool to help other countries in reducing their respective EKCs. In fact, policies and especially technologies and knowledge could be imported in less developing countries in order to avoid an excessive worsening of the environment—that could be induced by international trade too by carbon leakage and pollution heaven effects induced by more developed countries. However, this possibility could turn itself into a double-edge sword. In fact, while new cleaner technologies are able to reduce emissions per unit, if they are unfitting for the actual level of economic progress in the host country[73] could have opposite effect for example by reducing employment, thus rising the number of unemployed mass—mostly rural and less skilled labors—which return to deplete natural resources or producing highly polluting combustibles. Technology transfers require to be adapted to the structural state of the hosting countries with necessary efforts to improve human capital as well. In the same way of technology transfer, even the implementation of environmental policies inspired by those adopted in more advanced countries should be cautious and appropriate for the development phase of beneficiary countries. In this context, a gradual transition to international environmental standards through flexible marked-based instruments, incentives and disincentives rather than rigid command and control policies would be a best

[73]These technologies are usually designed under circumstances of high-cost labor and low-cost capital while poor countries usually present an opposite conformation.

solution to avoid counter-productive results. Moreover, even international support for less developed countries is a feasible solution by financing local projects and Grossman and Krueger (1996) agreed with this idea as well.[74] The REDD+ program for example, although highly debated, is considered by Culas (2012) a tool that could effectively turn to be useful in tunneling the EKC in the case of deforestation if implemented properly.

1.3.4 Skepticism and criticisms

The position of the WB in 1992 regarding the relation between economic growth and the environment and the subsequent emergence of the EKC was obviously not without critiques. After all, previous paragraphs already evidenced some flaws of this hypothesis of how the curve could assume different shapes and how the turning point is not obvious. One of the first critical view was the one of Arrow *et al.* (1995) which evidenced main weaknesses of this theory with some interrelated arguments. First, the validity of EKC only for concentrated pollutants involving short-term costs not dispersed in area and spread over long period of persistence. Second, the relation of this hypothesis which does not hold for resource stock such as soil and forest. Third, the fact that reduction in emissions could be a result of a simple leakage effect due to international trade, thus the absence of a system-wide consequence perspective of this theory. In general, although Arrow *et al.* (1995) do not confute that some countries for specific pollutants experienced the EKC, they were reluctant to view this as a general path that occurs in all cases and times. Grossman and Krueger (1996) replied to these critiques remarking how nothing is automatic about the relationship between economic growth and the environment. While the former group of academics posed on a possible environmental dumping beyond the EKC, the two authors pointed out the lack of empirical evidence to support this critique, rather emphasizing positive technological trade-off pursued through international trade. Ultimately, these two conclusions seem to be not the antipodes. In fact, while for Arrow *et al.* (1995) "economic growth is not a panacea for the environmental quality [and] economic liberalization and other policies that promote GNP growth are not substitutes for environmental policy" [p.93], Grossman and Krueger (1996) stated that "neither is the suppression of economic growth or of economic policies conductive to it a suitable substitute for environmental policy"

[74]They wrote: "Why not initiate an international fund to finance environmental protection in the poor countries reward those countries that provides signals to their resource users that encourage them to internalize the global externalities?" (Grossman and Krueger, 1996)[p.122].

[p.121]. The former position stressed the urge to focus on the limits of environment resilience and necessity of good institutions; the latter evidenced possible benefits of international trade and progress but also the aid that more developed countries could give to others in order to avoid over pollution and exploitation of natural resources. After all, they simply remark two sides of the same coin even though in the literature these positions seem to be seen as diametrically opposed.

The same way the EKC literature flourished after the first works in the early nineties likewise has been for a literature of criticism of this hypothesis. While Arrow *et al.* (1995) have been the first on this critical front, Stern (2004) is probably one of the most fervid authors dissenting with the EKC. In his first work, Stern *et al.* (1996) pointed out main flaws of this hypothesis testing the EKC with forecasted data (WB, 1992) based on Panayotou's first work over the period 1990–2025. Their findings stated how SO_2 emissions will continue to rise for the whole period[75] while total forest loss will eventually stabilize at the end of the period but without a reduction in tropical deforestation rates. The work of Stern (2004) represents probably one of the most comprehensive critical reviews of the EKC and recently, after 25 years from the beginning of the EKC, a new one followed (Stern, 2017). In both cases the author suggests alternative approaches to modeling the income-emissions relationships: decomposition and convergence analysis.

EKC critiques could be divided into two broad categories: theoretical and econometric. The former question the idea of the EKC while the latter the models' robustness. Here are listed and summarized the main problems raised by literature.

1. The first theoretical critique relies on the primer work of Arrow *et al.* (1995), focused on questioning the *assumption* that economic growth itself could be sustainable without concern for the environment since it is assumed as an exogenous variable, thus without concern for natural resilience and reversibility.
2. Linked to the first general point, the use of *GDP* has been strongly criticized—not only in this literature—because it is not considered a good indicator to identify the effective development level of a country since GDP per capita is not normally distributed among population but very skewed. In fact, high number of people live—especially in less developed countries—under the level of GDP per capita, thus the use of median income instead of mean could be a more appropriate measure (Stern *et al.*, 1996). However, in the wide literature of the EKC there are some—probably few—works which try to test

[75] In another work, Stern and Common (2001) identified a GDP turning point for this gas higher than US$ 100,000.

different proxies of growth instead of the classic GDP. For example, the work of Costantini and Martini (2009) considers the Human Development Index (HDI) (UNDP, 2017) as a variable of well-being and the World Bank's genuine savings as a measure of sustainability. Furthermore, even the work of Jha and Murthy (2003) faces the EKC using the HDI but with an interesting composite Environmental Degradation Index (EDI) as dependent variable.[76]

3. The third problem is related to the main environmental variable tested: *emissions*. Despite the fact that some emissions have declined over time, other new emissions occurred and for example from SO_2 and NO_x to CO_2 and solid waste, thus per capita emissions and waste may not have declined (Stern, 2004). Furthermore, Panayotou (1993) stressed the importance in distinguish between emission and concentration of pollutions. In fact, the question of emissions is related also to how those are calculated since more concentrated pollutions are easy to identify with a specific area. In the long run more dispersed pollutants decrease slowly an several works confirm this finding, eventually with truly high turning point (*e.g.* Holtz-Eakin and Selden, 1995; Shafik, 1994). As note by Carson (2010): "because CO_2 is a global rather than a local externality, it was simple to explain why it showed, at best, a weak EKC relationship. Thus, SO_2 became the poster child for the EKC relationship" [p.15]. However, the attention to SO_2 has decreased over time considering the rising global attention related to CO_2.

4. Strictly related and subsequent to the previous point, is the matter of *data quality* and coverage, a common "plague" for much economics. Early works on EKC have been characterized by a panel of data (GEMS) mainly composed by developed countries, thus the attention to less developed countries was initially scarce, but now these countries are those that require the highest attention since they are suffering the most pollution and natural resources depletion the most (Carson, 2010). Data problems are related not only to pollutants but even for natural resources, first of all forest cover. In fact, although Munasinghe

[76] Theoretical critiques have been moved even against microeconomic models which aims to explain the path of the EKC by means of particular assumptions, an easy way to justify the bell-shape path of this hypothesis according to Stern (2004) but without empirical tests. However, even among authors which developed these models there are some critical positions. For example, McConnell (1997) pointed out how the positive income elasticity of demand for environmental quality is not necessarily nor sufficient to verify the reverse U-shape relation of the EKC.

(1999) pointed out how the fact that forests are easily ascribed to countries, their quality and time-span are weak ar remarked by Shafik (1994).[77]

5. *International trade* also represents a core criticisms of the EKC since the shift of more pollutant activities and the depletion of natural resource in less developed countries could justify the evidence of the reverse U-shape in more wealthy countries. This would lead to two related effects: pollution heaven and carbon leakage. Developed countries move their pollutant activities to developing countries (pollution heaven) attracted by their less stringent environmental regulations. In this way developed countries may reach their EKCs' peaks faster without relying, for example, on technological improvements. The emissions produced by more industrialized countries reduce while increase in less developed countries with less stringent environmental regulations because because pollutants have not been overthrown but simply shifted (leakage effect). However, today poor countries will not have the opportunity to do the same as they become wealthy since the limitation of a finite world. Grossman and Krueger (1995) are aware of the possibility of an environmental dumping through international trade; however, this phenomenon according to the authors it too small to account for the reduced pollution occurred in countries which experimented the EKC. Furthermore, albeit evidence of pollution heaven and carbon leakage effects have been evidenced by examining North-South trade flows, Cole (2004) concluded that this dumping effect is small compared to other EKC explanatory variables.

6. Last but not least, several critical aspects moved against the EKC are econometrics. The first and main econometric critique poses on the *econometric model* used to test them. Since EKC models are mainly focused on country-level analysis, they are mainly tested by using fixed effects panel data model. This choice allows to carry out consistent estimates—assuming the absence of other econometric problems—but strictly conditional to individual and time effects of the specific sample in exam (Hsiao, 2014), thus the impossibility to do inference. Using panel data fixed effect, the underlying assumption is that individuals (countries) are characterize by same growth levels and environmental development paths, thus in absence of these coincidences results would be uncertain and the choice to conduct time-series analysis of a panel for similar countries would be a more suitable choice (Bo, 2011). List and Gallet (1999) confirmed this uncertainty conducting a state-level study for United States

[77] Chapter 2 deepen problems related to forest cover data.

per capita emissions of SO_2 and NO_x from 1929 to 1994.[78] Their results show the existence of an inverted U-shape relation but peaks and turning points result to be thoroughly different from previous studies highlighting how more specific analysis can lead to different results compared to classic cross-section country models.

Following this model-critique, other two econometric problems have been moved by Stern (2004) against EKC models: *heteroskedasticity* and *omitted variables bias* (*e.g.* Wooldridge, 2015). The former has been first raised by Stern *et al.* (1996) since observation which are aggregation of various number and subunits—like those from the GEMS database—are prone to suffer from this problem. The latter has been addressed by in Stern and Common (2001) where has been demonstrated how the EKC turning point highly differentiated among fixed and random effects results, different subsample,[79] and with tests for serial correlation (first differences).

Moreover, another fundamental problem is the effective *causality* between income and environmental degradation. The Granger causality (1980), or rather whether a change in one variable occurs before changes in another dependent variable and thus help to predict it, represents the main tool to verify this assumption. Only recently this issue has been addressed in the literature (*e.g.* Perman and Stern, 2003) showing how income could be an integrated variable (nonstationary) which leads to spurious results. Furthermore, Granger causality could imply that variables must move together, thus be cointegrated (Nelson and Plosser, 1982). Stern (2004) stressed the importance to test for *cointegration*, usually not considered among EKC studies since the attention to times-series structure in early EKC works was not taken into account (Carson, 2010). However, despite these critiques some works evidence a possible existence of an EKC for CO_2 emissions facing in-deep the question of cointegration (*e.g.* Galeotti *et al.*, 2009).[80]

Eventually, econometric flaws have been evidenced by Harbaugh *et al.* (2002) which extended the original GEMS dataset of Grossman and Krueger (1991)[81] concluding how their EKC was much less robust than previous works,

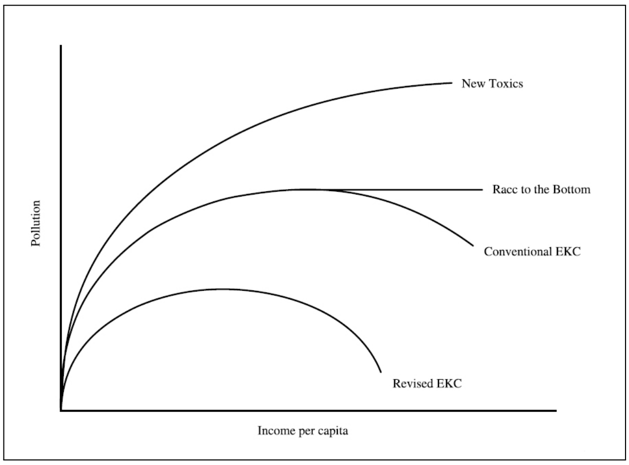
[78] They used data retrieved from the US Environmental Protection Agency (EPA, 2017).

[79] The authors considered the following groups: world, OECD, and non-OECD countries.

[80] According to Stern (2004), econometric critiques to EKC could be grouped into four main categories: heteroskedasticity, simultaneity, omitted variables bias, and cointegration issues.

[81] The authors extended the year coverage of the original database; furthermore, they corrected and integrated data values.

Figure 1.12 *EKC: alternative views*



Source: Perman and Stern (2003)[p.327] based on Dasgupta *et al.* (2002).

sensitive to data variation and econometric specifications. Furthermore, Carson (2010) stressed how these critiques commit with the review of Levine and Renelt (1992) which evidenced how "a vast literature uses cross-country regressions to search for empirical linkages between long-run growth rates and a variety of economic policy, political, and institutional indicators" [p.942] but, eventually, with fragile results.

In conclusion, the whole critique side of the EKC could be summarized with the words of Stern (2017) "the EKC is an essentially empirical phenomenon, but most estimates of EKC model are not statistically robust. Concentrations of some local pollutant have clearly declined in developed countries but there is much less clarity about emissions of pollutants and there is still no consensus on the drivers of changes emissions" [p.2].

However, a different critical review of the EKC proposed by Dasgupta *et al.* (2002) stressed out possible alternative trends for the EKC as showed in Figure 1.12, thus a different conclusion about this debate. Conversely to the *conventional EKC*, the *new toxics* scenario does not show the inverted shape such as for CO_2. Furthermore, the *race to the bottom* scenario is associated with the problem of international trade, thus the pollution reduced in developed countries obtained by displacing less clean activities to developing countries. Lastly, the *revised EKC* represents a downward shift of the classic reverse U-shape curve, thus with flatter and shorter peaks meaning less environmental degradation reached with lower level of income. This scenario is justified by the fact that globalization and freer markets has fostered the implementation of more stringent regulation and the diffusion of clean technology in developing countries able to achieve a better EKC which seems to contradict the "race to the bottom" scenario.[82]

Critiques to the EKC have been mainly focused to his direct causality between economic growth and environmental degradation stressing, from different perspective, how it could be wrong to follow this simplistic assumption. It is undoubtedly wrong that economic growth itself could lead to a decrease in environmental degradation and it has been—maybe sometimes forgotten—even the position of early works on EKC despite the fact that their model mainly focused only on GDP. Moreover, after a quarter of century from the first proposition of this hypothesis, data has changed and enhanced both in quantity and quality while econometric approaches have been widespread and improved becoming more and more better tools—although growing in complexity. Therefore, the debate around the EKC still continues, maybe because of its straightforwardness, with new findings and tools. Positions regarding the EKC are not always clearly defined. Carson (2010) tried to identify a pessimistic and an optimist view. The former, poses and criticized the autonomous assumption that economic growth could sustain the environment itself, from the first work of Arrow *et al.* (1995) to the latest Stern (2017). The latter, instead, switches the attention to other factors and do not intend the EKC in its typical reduced-form but focuses more on other driving forces—undoubtedly related with development—able, for developing countries, not only to flatten the curve but even to shift it to the left as proposed by Dasgupta *et al.* (2002). Nonetheless, since the main literature on the EKC has mainly focused on gas emissions rather than natural resource depletion, such as forests, thus this aspect of environmental degradation probably deserves to be addressed more.

1.4 The EKC for deforestation

Moving to the true EKC of interest, the one for deforestation has the identical shape of the curve presented in Figure 1.8: the x-axis represents the economic growth of the country, expressed in GDP levels, while the y-axis reports the environmental degradation, in this case forest losses. Several possibilities are proposed in literature to quantify this variables. Here a brief summary of different solutions proposed in the literature are reported. The more authoritative identification of deforestation, the annual rate of forest change q, is the one provided by FAO (1995b). It is obtained by comparing the forest area of the same region in two different times as showed

[82]Evidences for their conclusions have been mainly retrieved from China.

in equation 1.4 where A_2 and A_1 represent the area of forest cover at time t_2 and t_1 respectively. However, Puyravaud (2003) proposed a slightly different standardization for this variable with a more intuitive equation derived from the Compound Interest Law and the mean annual rate of change (eq. 1.5) named r.[83]

$$q = \left(\frac{A_2}{A_1}\right)^{\frac{1}{t_2-t_1}} - 1 \quad (1.4) \qquad r = \frac{1}{t_2 - t_1} log \frac{A_2}{A_1} \quad (1.5)$$

Concerning the EKCd, the importance is given to the annual deforestation rate or change in forest cover; therefore, the time component of equations 1.4 and 1.5 reduces to one resulting only in the ratio between the forest area in two subsequent time periods t_{-1} and t. The first literature's work of Shafik and Bandyopadhyay (1992) used the annual rate of deforestation expressed in natural logarithms (eq. 1.6). This indicator, used even by Cropper and Griffiths (1994) (but not in logs), represents the main indicator employed in literature (*e.g.* Koop and Tole, 1999; Bhattarai and Hammig, 2001; Culas, 2012). The recent work of Leblois *et al.* (2017) considered the yearly forest cover change divided by the land area of the country to standardize values among individuals, expressed in logs (eq. 1.7).[84] Recent literature used also log-value of total forest area (eq. 1.8) as dependent variable (Joshi and Beck, 2016). This indicator could be improved following the suggestion of Hyde (2012) which proposed the inverse of forest cover per capita (eq. 1.9) or unit of area (eq. 1.10) to account for environmental degradation related to forest losses. However, the same author pointed out how cross-country comparisons made in physical stock would lead to biased result since national definitions of forest stock change widely among states, thus he suggests to rely on rates or year changes in national measure of forest instead. Furthermore, since agricultural expansion represents the main cause of deforestation (70%) in tropical countries (FAO, 2001b), even agricultural area has been used as a proxy for deforestation. For example, Barbier and Burgess (2001) consider the forest cover change as the opposite of the year change of agricultural area (eq. 1.11) or its rate (eq. 1.12) (Barbier, 2004). Eventually, even arable land has been used as a proxy to account for deforestation (Chiu, 2012) (eq. 1.13) which could be seen as the opposite of equation 1.8. Here are listed the main variables used to

[83] The rate r is always higher than q, especially when the deforestation process is forceful.

[84] Note that the use of logs in this formula is possible since the authors considered only losses in forest cover changes and not cases of reforestation.

quantify deforestation or forest losses among EKCd studies:

$$log(For_{i,t-1}) - log(For_{i,t}) \tag{1.6}$$

$$log\left(\frac{For_{i,t} - For_{i,t-1}}{Land_{i,t}}\right) \tag{1.7}$$

$$log(For_{i,t}) \tag{1.8}$$

$$\frac{1}{\frac{For_{i,t}}{Pop_{i,t}}} \tag{1.9}$$

$$\frac{1}{\frac{For_{i,t}}{Land_{i,t}}} \tag{1.10}$$

$$F_{it} - F_{it-1} = -(A_{it} - A_{it-1}) \tag{1.11}$$

$$\frac{Agri_{i,t} - Agri_{i,t-1}}{Agri_{i,t}} \tag{1.12}$$

$$log(Arable_{i,t}) \tag{1.13}$$

The solution proposed by Puyravaud (2003) (eq. 1.5) is equivalent to the one used by Shafik and Bandyopadhyay (1992) (eq. 1.6) when $t_2 - t_1 = 1$ resulting in a simple yearly deforestation rates obtained by a log difference between forest cover in $t_{-}1$ and t_1.

Eventually, regarding independent variables, GDP per capita obviously represents the core variable of interest in this literature, expressed in linear, quadratic and sometimes cubic forms. Therefore, various additional right-hand variables, for both explicative and control purposes, could be retrieved within the literature of the EKCd. Among others are commonly included the following variables: population, agricultural land and products, forests products, international trade, and institutions. In the following paragraphs, carrying out a review of the main works which investigated the EKCd, the choice of these variables will be presented as well.

1.4.1 Main literature on the EKC for deforestation

The bulk of the literature have focused the analysis on tropical and developing countries, clustering them according to geographical area: Africa, Asia, and Latin America even though more recent works contemplate also developed countries. The following section summarizes the core works of the EKC literature related to deforestation considered within the meta-analysis carried out by Choumert *et al.* (2013). They considered 69 studies which have been dealing with deforestation and the EKC showing how more recent results tend to refuse the possible existence of a reverse U-shape relation between deforestation and economic growth. However, their assessment also evidenced how different and opposite results characterize this branch of the EKC due to different choices made by the authors such as econometric approach, forest data and measure of deforestation, geographical area, and use of control variables.

The first application in literature of the EKCd as an environmental degradation has been made by Shafik and Bandyopadhyay (1992). They evaluated both yearly and total forest loss. The former for 66 countries from 1962 until 1988, the latter for 77 countries from 1961 until 1988.[85] Using a panel fixed effect methodology the authors performed three basic models for each pollutant: log-linear, -quadratic, and -cubic. Furthermore, a time trend variable has been added alongside various additional covariates, each of them in a separate equation. The first graphical representation of the famous EKC for deforestation (rates and total deforestation) is showed in Figure 1.13.[86] However, despite the signs of their regressions are in line with the EKC, there is no statistical significance of the coefficients.

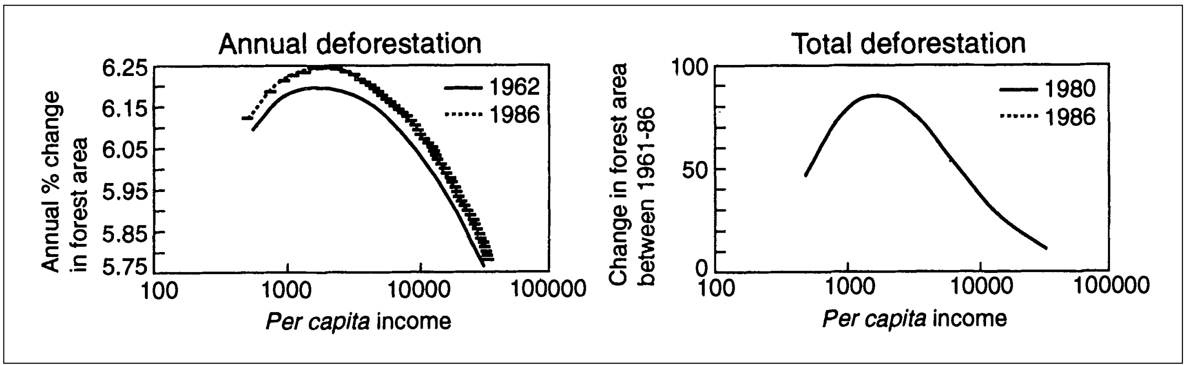
The second proposition of the EKCd could be found in Panayotou (1993), where the author carried out a log-log OLS estimation for 41 tropical countries using mid-to-late 1980s deforestation rates (WRI, 1991). Including also the population variable in the regression, the author concluded for the existence of an inverse U-shape relation with a turning point at US$ 823 as showed in the graphical representation of Figure 1.14 where the lower value across the curve is occupied by Ethiopia and the higher by Venezuela.[87]

[85]The authors retrieved data from the data appendix of WB (1992).

[86]The figure reported has been retrieved from a subsequent source (Shafik, 1994) due to a better graphical resolution, but it is equivalent to the one first proposed in Shafik and Bandyopadhyay (1992).

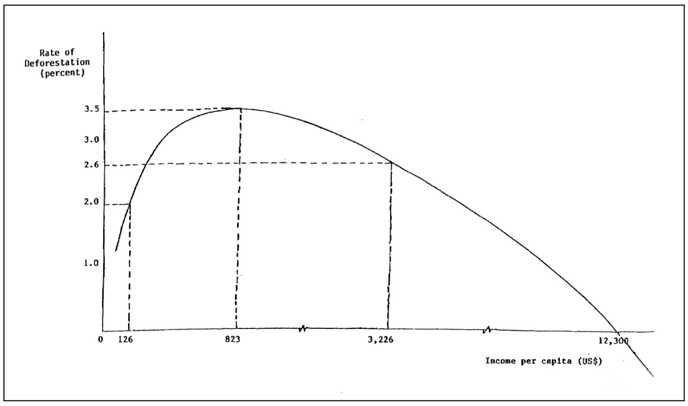
[87]Note that the apparently low level of turning point founded in this work is due to the fact that Panayotou (1993) used current exchange rates instead of PPP to express GDP levels.

Figure 1.13 *EKC for deforestation rates and total deforestation (1986-1982)*



Source: Shafik (1994)[p.764].

Figure 1.14 *EKC for tropical deforestation*



Source: Panayotou (1993)[p.8].

However, the very first work focused only on the EKCd has been carried out by Cropper and Griffiths (1994). They were the first in using forestry data retrieved from the *FAO Production Yearbook* (FAO, 1995a), a common source for these analysis.[88] They estimated a fixed effect model over the period 1961–1988 for a panel of 64 tropical countries—those with more than 1,000,000 hectares of forest cover[89]—including the linear and quadratic term of GDP per capita, change in capita income, price of tropical logs, rural population density, and change in population. Their results evidenced an EKC for Africa and Latin America with peaks of US$ 4,760 and 5,420, respectively. Concerning Africa, the positive coefficient of rural population stressed how its density increases pressure on forest resources. The rate of growth had a slightly negative effect on deforestation for these two countries while the price of tropical logs is statistically significant and has a positive impact only for Latin America, a country where logs occurred on much larger scale. Conversely, the Asian

[88]Criticisms about this source are addressed in Chapter 2.
[89]Developed countries have been left out due to difference in forest cover estimation.

cluster represented a kind of "anomaly" due to the absence of significant results justified by elevated amount of forest plantations which supposedly affected the results.[90] Eventually, the two authors clearly stressed how the two identified turning points were quite high and without policy intervention an huge amount of forest loss could potentially occur before they can be reached.

Koop and Tole (1999) performed a similar analysis of the one proposed by Cropper and Griffiths (1994) but with a slightly wider database composed by 76 tropical developing countries over the period 1961–1992. The authors stressed one of the main econometric problems related to the EKC, the fact that fixed and random effects leads to model with restrictive assumption, or rather that each country follow the same path of the curve. In order to do so, alongside the pooled, fixed, and random effects models they proposed also a random coefficient model (Swamy, 1973) which specified that each country has its own EKC. For each methodology two models have been performed: the first one (basic model), composed only by the linear and quadratic terms of GDP; the second one (extended model), enlarged with GDP growth, population density, and population growth. The pooled method is strongly rejected in favor of the fixed effects where only for Latin America the EKC is supported. With random effects, the EKC is confirmed for the whole sample of countries, Africa, and Asia while for Latin America the fixed effects model is preferred. However, these models are rejected in favor of the random coefficients model which gives no statistical support for the reverse U-shape relation due to high heterogeneity among countries.[91]

An important work in this literature is the one of Bhattarai and Hammig (2001) for the introduction of several additional explanatory variables in the analysis by means of various proxies. Besides population variables they added also the level of institutions (the sum of political rights and civil liberties indices), agricultural technological change (change in cereal yield), trade policies and exchange rates (black market premium on foreign exchange), and debt over GDP. Their analysis is similar with the one of Cropper and Griffiths (1994), with the same forest data source and a group of 63 tropical countries studied over the period 1972–1991. Results for the EKC shapes are also in line with Cropper and Griffiths (1994) although the addition of the cubic terms of GDP per capita resulted in an N-shape gait for Africa and Latin America and a reverse N-shape for Asia. For Latin America the

[90] In fact, FAO (1993) estimated that in 1990 the amount of natural forest in this region decreased by 3,9 million he while an amount of 2,1 million he of plantations were established.

[91] By rejecting a common structure across countries (equal coefficients), country-specific coefficients results remarkably different from the average values.

first turning point is reached around US$ 6,600. Africa reaches its first peak at US$ 1,300 but after US$ 3,500, the second turning point, a new environmental worsening occurred. Concerning Asia instead, the first peak lies around US$ 2,200 while the second at US$ 5,500 which is associated with a decrease in deforestation due to the reverse curve's shape for these countries. Moreover, political institutions have a positive effect in reducing forest loss in Africa and Latin America and the same sign result even for population growth conversely to rural population density. For these variables the Asian cluster have complete opposite signs and the only variable with the same negative effect for the three groups resulted to be the debt over GDP. Eventually, a similar analysis but with different forestry data and additional explanatory variables[92] has been carried out in a subsequent work (Bhattarai and Hammig, 2004) concluding for the existence of a EKC for tropical countries with turning points between US$ 6,000 and 7,000.

The work of Barbier and Burgess (2001) is peculiar for its purpose to synthesize in an unique model four different approaches to cross-country analysis related to forest cover change: the EKC analysis, the competing land use model,[93] the forest land conversion model,[94] and the institutional model.[95] It must be noticed that these approaches could be connected, from different perspectives, to the FDP. One of the main characteristics of Barbier and Burgess's model is the use of agricultural land change to account for forest cover losses[96] over a time span which runs from 1961 to 1994 for 90 tropical countries. Further explanatory variables are focused in capturing country-by-country differences in agriculture and land use changes, economic and population growth, and institutions. Since this latter variable was time invariant[97] two different models have been carried out: one with a panel fixed and random

[92]Respect to their previous work, forest cover data has been retrieved for the years 1980, 1990, and 1995 from WRI (1999). Furthermore, they added the following variables: governance, agricultural value added, secondary school enrollment, annual inflation rate, real exchange rate, and terms of trade.

[93]Focused on the study of forest loss in tropical countries as the result between natural forest and agricultural activities (*e.g.* Barbier and Burgess, 1997).

[94]Based on the forest land conversion decision of farmers which is a function of input and output prices, agricultural wages, and other factors such as roads, infrastructure, and distance to cities (*e.g.* Barbier and Burgess, 1996; Chomitz and Gray, 1996; Cropper *et al.*, 1999).

[95]Focused on the investigation of how institutional factors such as land use conflict, proper rights, and rule of low could affect deforestation (*e.g.* Alston *et al.*, 2000).

[96]Under the assumption that:

$$F_{it} - F_{it-1} = -(A_{it} - A_{it-1}) \tag{1.14}$$

Where F stands for forest area and A for agricultural area.

[97]Retrieved from the Levine-Loayaza-Beck data set (Beck *et al.*, 2000).

effects without institutional variable, and another with OLS techniques and the inclusion of these additional right-hand variables. Results among the two models are quite different since in the first one the EKC is confirmed only for Asia (turning point US$ 6,182) while in the second model the EKC is confirmed for the whole country sample (US$ 5,445) and for Latin America (US$ 4,946) but not for Africa and Asia. Eventually, a successive work of Barbier (2004) used a similar methodology to assess forest losses: the percentage change in agricultural area, but enlarging the time span to 1961–1999 and considering also terms of trade. However, results from this following work confuted a possible EKC for tropical countries.

A useful overview of the EKCd could be found in the works of Culas (2012) and Leblois *et al.* (2017) that summarized main works of this literature. A similar graphical survey is proposed in the following Chart 1.1. Moreover, Culas's work is interesting for two main reasons: first, he investigated the EKC by embracing the FT hypothesis at the same time; second, because he suggested a possible flattening of the EKC—and a shorten forest transition period—through the incentives from REDD policies. Following previous studies, forestry data source for this study relies on the FAO Production Yearbook (FAO, 1995a) for 43 tropical countries between 1971 and 1994. Furthermore, the model attempts to consider the two FT's paths suggested by Rudel *et al.* (2005): the relation between deforestation rates and GDP for the *economic development path* and two additional forest explanatory variables, absolute and proportion of forest area, for the *forest scarcity path*.[98] The result, in accordance with previous works, confirmed the presence of an EKCd for Latin America and Africa, with turning point of US$ 1,483 and 6,072, respectively, but a reverse relation for Asia.

Figure 1.15 helps in concluding this section by retracing the evolution of the EKC for deforestation from 1992 up to 2012. Choumert *et al.* (2013) identified a turning point in 2001 where the literature started to switch from a general corroboration of the EKC validity to a more skepticisms and rejection. This is mainly explained by improvements in econometric analysis and data, from *FAO Production Yearbook* to *Forest Resource Assessments* data, generally considered a more reliable source. However, the authors interpreted the EKC theory in a "Popperian" way predicting that its fate is all but expired. A still lively theory which will be probably adjusted in order to face new raised problems and anomalies.

[98] See Section 1.5 for further details.

Table 1.1 *Main cross-country studies on the EKC for deforestation*

Author(s)	Estimated model(s)	Countries	Time period	Dependent variable and data	Estimation method(s)	Existence of inverted U-shaped EKC	Turning point(s) in US$
Chiu (2012)	Quadratic	52 developing countries	1972–2003	Arable Land (FAO)	FE with PSTR	Yes	3.021 3.103
Culas (2012)	Quadratic	43 tropical developing countries	1971–1994	Deforestation rates (FAO Production Yearbook)	FE	Yes: Africa and Latin America No: Asia	6,072 (Africa) 1,483 (Latin America)
Damette and Delacote (2012)	Quadratic	59 developing countries	1972–1994	Deforestation rates (FAO Production Yearbook)	OLS and FE	Weak[1]	n.a.
Damette and Delacote (2011)	Quadratic	87 countries	1972–1994	Deforestation rates (FAO Production Yearbook)	FE and double FE	Yes: all countries No: developing countries [2]	n.a.
Motel *et al.* (2009)	Quadratic	48 tropical developing countries	1970–2005	Natural forest deforestation rates (FAO, 2006a, 2017a)[3]	FE	Yes	n.a.
Culas (2007)	Quadratic	14 tropical developing countries	1972–1994	Deforestation rates (FAO Production Yearbook)	OLS, FE, and RE	Yes: Latin America No: Africa and Asia	n.a.
Van and Azomahou (2007)	Quadratic	59 developing countries	1972–1994	Deforestation rates (FAO Production Yearbook)	FE	No	n.a.
Barbier (2004)	Quadratic	90 tropical countries	1960–1999	Agricultural land change rates (WDI of WB)	RE	No	n.a.
Meyer *et al.* (2003)	Quadratic	117 countries	1990–2000	Deforestation rates (FAO, 2001b)	OLS	No	n.a.
Ehrhardt-Martinez *et al.* (2002)	Quadratic	74 LDC countries[4]	1980–1995	Deforestation rates (FAO, 1995b; WRI, 1999)	OLS	Yes[5]	1,150
Barbier and Burgess (2001)	Quadratic	90 tropical countries	1961–1994	Agricultural land change (WDI of WB)	OLS, FE, and RE	Yes: all countries, Asia, and Latin America No: Africa	5,445 (all countries) 6,182 (Asia) 4,946 (Latin America)
Bhattarai and Hammig (2001)	Cubic	66 tropical countries	1972–1991	Deforestation rates (FAO Production Yearbook)	FGLS	Yes: Africa and Latin America No: Asia	1,300 (Africa) 6,600 (Latin America)
Koop and Tole (1999)	Quadratic	76 tropical developing countries	1961–1992	Deforestation rates (FAO Production Yearbook)	OLS, FE, RE, and RCM	Yes: Latin America No: all countries, Africa, and Asia[6]	8,660
Antle and Heidebrink (1995)	Quadratic	82 countries	1980–1984	Parks and afforestation (UNEP, 1990; WRI, 1991)	OLS	Yes	1,200-2,000
Cropper and Griffiths (1994)	Quadratic	64 tropical non-OECD countries	1961–1988	Deforestation rates (FAO Production Yearbook)	FE	Yes: Africa and Latin America No: Asia	4,760 (Africa) 5,420 (Latin America)
Shafik (1994)	Linear, quadratic, and cubic	66 countries	1962–1986	Deforestation rates (WB, 1992)	FE	No	n.a.
Panayotou (1993)	Quadratic	41 tropical countries	Late 1980s	Forest cover change (WRI, 1991)	OLS	Yes	823

Notes: FE: Fixed Effects model; FGLS: Feasible Generalized Least Squares; OLS: Ordinary Least Squares; PSTR: Panel Smooth Transition Regression; RE: Random Effects model; RMC: Random Coefficient model; n.a. means that information is not available.

[1] EKC for deforestation appears to be valid for high deforestation observations only.

[2] Evidence for an EKC is found when the Harvest-volume variable is used, but not with the Harvest-value variable.

[3] Data for the periods 1970-1990 has been retrieved from FAO. However, actually this source provides forest cover data only for the period 1990-2015.

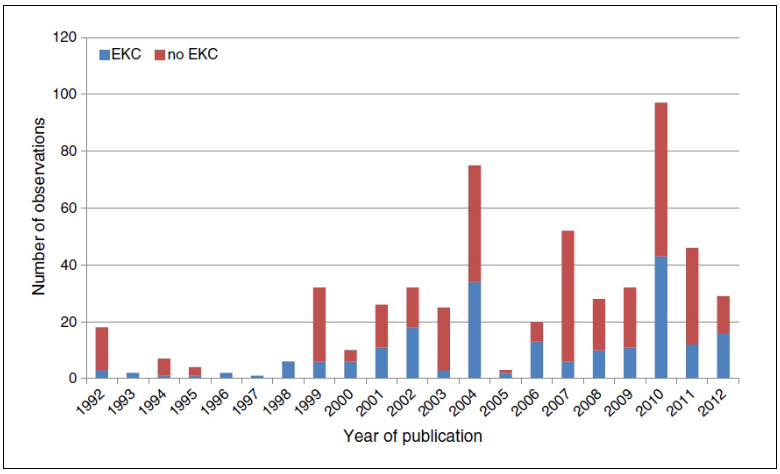
[4] Least Developed Countries.

[5] Out of 18 models proposed, only the first two deal with the EKC. However, when population variables are included in the model, the EKC is no longer statistically significant.

[6] Using the RCM the EKC is no longer verified.

Source: Author's personal elaboration based on the work of Culas (2012) with some addiction retrieved from a similar table proposed in Leblois *et al.* (2017). Note that only cross-country works with a classical EKC structure has been considered.

Figure 1.15 *Empirical analyses of EKCs for deforestation*



Source: Choumert *et al.* (2013)[p.20].

1.4.2 Recent developments of the EKC for deforestation

After the wide review of the EKCd made by Choumert *et al.* (2013), its application for deforestation still continues, even if a numerical comparison with other pollutants remains peerless. Here are presented the more recent development of the literature of the EKC in its deforestation perspective.

The work of Joshi and Beck (2016) tested the EKC hypothesis by using FRA 2010 data (FAO, 2010b) for the period 1990–2007 for OECD and non-OECD countries considering total forest cover as left-hand and GDP per capita as right-hand variables alongside population growth, terms of trade,[99] agricultural land, and cereal yield as other explanatory variables. They performed a dynamic panel data GMM (Generalized Method of Moments) estimation[100] for four country clusters: Africa (11), Asia (7), Latin America (14), and OECD (20). Results show the existence of the reverse U-shape curve only for African countries while results for OECD countries, despite their past FT experience, show an N-shape tendency, thus a return of deforestation. Latin American countries show a similar path while for Asia GDP per capita seems to be not significant. Population growth has a negative and statistically significant impact for Africa, Asia, and OECD countries as well as for urban populations, but only for Asia. Furthermore, agricultural land has a negative impact for Latin America and OECD countries, but positive for Africa while cereal yields results to have a positive and significant impact only for OECD economies. Eventually, trade has a

[99] Net barter terms of trade index (2000 = 100) (WB, 2017).

[100] Specifically they used the Arellano-Bover/Blundell-Bond GMM estimation (Arellano and Bover, 1995; Blundell and Bond, 1998).

positive impact on forest cover for Africa but negative for Latin America and OECD countries.

Ogundari *et al.* (2017) focused their research on 43 Sub-Saharan Africa countries trying to revisit the EKC both for deforestation and GHG emissions from agriculture[101] for the period 1990–2009 with deforestation data obtained from FAO (2017a).[102] Alongside real GDP per capita in linear and quadratic form, right-hand variables employed for the analysis are agricultural production,[103] trade openness, population and GDP growth, and political liberty. The model, a fixed effects Feasible Generalized Least Squares (FGLS) (*e.g.* (Greene, 2002)), evidenced the existence of an U-shape relation only for agriculture emissions. Concerning deforestation, it increases with economic growth and the other independent variables concur to worsen forest environment. These results reflect the findings of Culas (2007) and Bhattarai and Hammig (2001) for Africa while gainsay those of Koop and Tole (1999), Shafik and Bandyopadhyay (1992), as well as the recent work of Joshi and Beck (2016).

Another recent regional-focused work conducted by Liu *et al.* (2017) studied the FT for nine Asian countries from 1960 to 2010[104] but considering also the presence of a quadratic element for GDP in their model—thus an investigation for a possible EKC as well. The work performed a specific OLS applied for each country instead of a panel data. The first analysis, only with economic variables, show no evidence for an EKCd and no significant results. Conversely, by adding other explanatory variables to the model (rural population density, population growth, agricultural land, cereal yield, forest protect laws, national forest plans or decrees, and forest product export and import value) GDP variables gain statistical significance. Observing the results, they point out a possible EKCd for Korea and Indonesia. However, these conclusions are few and weak considering that forest area in Indonesia is still declining. Eventually, the study demonstrates how Japan and South Korea achieved the FT before 1980s, China, India, Vietnam, and the Philippines only in recent years, while Indonesia, Malaysia, and Laos still have to reach their own FTs.

Cuaresma *et al.* (2017) used satellite forest cover data from 2005[105] to test the EKCd controlling for trans-border geo-climactic differences. The dependent variable

[101] Measured in $MtCO_2$ per capita equivalent.

[102] Authors retrieved data on 2013, thus forest cover data refers to FRA 2010 (FAO, 2010b).

[103] Net value per capita.

[104] A specific reconstruction of forest cover trends have been realized for each country considered and they all span through the time-frame specified approximately.

[105] Their data has been retrieved from the Moderate Resolution Imaging Spectroradiometer (MODIS) on NASA's Terra spacecraft.

used is a measure of the relative forest cover of neighboring countries. To make border forests comparable, environmental factors between neighbors countries have been kept constant (as much as possible) through the use of a Homogeneous Response Units (HRU) layer. The authors concluded for a robust existence of a U-shaped relationship between forest cover and GDP per capita. Other variables have been included in the model, such as economic and population growth, rural population density, rule of law, corruption, agricultural land, and exports of agriculture's raw materials. Of these, only the last one resulted significant and with a negative impact on forest cover. The turning point of the curve locates on a level of US$ 5,500.[106] However, the existence of an EKC is strong and verified only for the first half of the curve due to the presence of developed countries in the model which affects a robust evidenced the second half.

One of the latest work which investigated the EKC for deforestation—albeit not as main research goal—is the one of Leblois *et al.* (2017). They utilized satellite data of Hansen *et al.* (2013) over the period 2001–2010 for 128 developing countries. However, they considered only deforestations results[107] (negative change in forest cover between t and t_{-1}) divided by land area to normalize among individuals. Alongside GDP per capita, the model considers agricultural land, trade openness, crops production,[108] population and GDP growth, terms of trade, politic liberties, and government durability. The initial model considers only the linear term for GDP per capita, tested even with a dynamic GMM model (Arellano and Bond, 1991), which evidenced how GDP tends to increase annual deforestation alongside population and GDP growth and market openness, on the contrary of terms of trade. A second model pointed out how the quadratic form of GDP per capita is not statistically significant as well as its linear form, thus the authors conclude for a non evidence of an EKC for deforestation. Furthermore, the authors conducted some other test on specific country clusters to identity main causes of deforestations but with some less meaningful results.[109] Lastly, in order to sharpen the analysis

[106] PPP-adjusted 2005 international.

[107] Gains in forest cover were not considered.

[108] These variables have been lagged to avoid endogenity.

[109] The four groups are: Africa (47), Latin America and West Indies (24), Asia and Pacific (21), and Europe, with Central Asia, North Africa, and Middle East (36). GDP per capita increases deforestation for the first and last group. GDP growth has a similar effect but only for the last group where population growth has an opposite effect instead, conversely to Africa, Latin America, and West Indies. Agriculture has a major role in increasing deforestation for Asia and Pacific while production of crops in Europe and the other countries of this group. These negative effects are compensated by the positive role of terms of trade; the same positive effect could be seen even in the fourth group. Eventually, government durability leads to an increase in deforestation only for Africa.

and investigate the effect of trade, even agricultural and forest export values have been included in the model clustering countries according on which stage of the FT they are (Hosonuma *et al.*, 2012).[110] These last results pointed out the negative effect of agricultural exports which become positive for countries in the transition phase while forest exports result in no statistical significance.

Lastly, even if not specific focused on forests, the interesting work of Busa (2013) tested the EKC as a relation between economic growth and biological conservation through a quantile regression (Koenker, 2005)[111] and spatial filtering (Griffith and Peres-Neto, 2006) analysis. Biological conservation is expressed as the proportion of species conserved over time for a cluster of 35 tropical countries and as the proportion of forest remaining over time for an expanded dataset of 88 countries. Results support the parabolic path of the EKC for the two datasets. However, when the authors incorporate in the model a consumption correction of forest products, results cease to support the EKC. International trade helps to explain this outcome since wealthy countries tend to drive deforestation to poorer countries making the turning point of the EKC just an illusion. The work of Busa (2013) replicates and enriches the analysis of Mills and Waite (2009) in turn inspired by Dietz and Adger (2003). The latter represents the first study with the aim to investigate the relation between economic growth, biodiversity loss, and efforts to conserve biodiversity with a Kuznets' perspective for 35 tropical countries. However, Dietz and Adger (2003) confuted the existence of an EKC for biodiversity considering it theoretically impossible since there is no reversibility for loss species. The former improves the analysis of Dietz and Adger (2003) providing some evidences for the EKC but it fades when specific country dummies are included, thus conclusions are similar with those of Busa (2013).[112]

Specific case studies

More than in the past, some recent works on the EKCd are focused on specific countries case study; nonetheless, in small number if compared to specific country studies of the classical EKC. For example, Esmaeili and Nasrnia (2014) confirmed the

[110]They evidenced four stages: phase 1 (pre-transition), phase 2 (early transition), phase 3 (late transition), and phase 4 (post-transition).

[111]The use of the quantile regression analysis helps to overcome heteroskedasticity problems related to EKC.

[112]Dietz and Adger (2003), Mills and Waite (2009), and Busa (2013) refer to the same group of 35 tropical countries. Furthermore, authors conducted their analysis for the same time range of 1972-1992 since they use data from the Production Yearbook of FAO (1995a). An useful schematic comparison among these three works could be found in Busa (2013).

Table 1.2 *Recent cross-country studies on the EKC for deforestation*

Author(s)	Estimated model(s)	Countries	Time period	Dependent variable and data	Estimation method(s)	Existence of inverted U-shaped EKC	Turning point(s) in US$
Cuaresma *et al.* (2017)	Quadratic	189 countries	2005	Vegetation Continuous Fields (Satellite forest cover data retrieved from MODIS, NASA)	Trans-border geo-climactic differences with HRU	Yes	5,500
Leblois *et al.* (2017)	Quadratic	128 countries	2001-2010	Deforestation change / Land area (Hansen *et al.*, 2013)	FE	No	n.a.
Liu *et al.* (2017)	Quadratic	9 Asian countries	1960-2010	Deforestation rates (FAO, 2010b and national inventories)	OLS	Weak support for Indonesia and South Korea	n.a.
Ogundari *et al.* (2017)	Quadratic	43 Sub-Saharan African countries	1990-2009	Deforestation rates (FAO, 2010b)	FGLS	No	n.a.
Joshi and Beck (2016)	Quadratic	47 OECD and non-OECD countries	1990-2007	Forest Area (FAO, 2010b)	GMM	Yes: Africa No: Asia, Latin America, and OECD	n.a.

Notes: FE: Fixed Effects model; FGLS: Feasible Generalized Least Squares; GMM: Generalized Method of Moments; HRU: Homogeneous Response Units; OLS: Ordinary Least Squares; n.a. means that information is not available.

Source: Author's personal elaboration.

existence of a reverse U-shape relation between deforestation and economic growth for Iran during the period 1976–2006 with an estimated turning point equal to US$ 24,555 through the use of an Autoregressive Distributed Lag (ARDL) model (Greene, 2000). Another study investigated the EKCd in Iran for the period 1986–2010 as well for atmosphere and water pollution[113] (Taghvaee and Shirazi, 2014). Through an OLS estimation the authors concluded for the existence of the EKC hypothesis for all of the three environmental degradation variables. Concerning deforestation—for which for the authors represent the variable of land degradation—is particularly confirmed the second half of the curve.[114]

Moreover, Ahmed *et al.* (2015) investigated the link between deforestation and trade openness for Pakistan during the time frame 1980–2013 alongside population density, energy consumption,[115] and trade openness in addition to GDP per capita. Authors used the ARDL bound test for cointegration (Pesaran *et al.*, 2001) to carry out their specific analysis of the long-run equilibrium relationship among

[113]Time frames considered for the three dependent variables are different since they have been tested separately. As concern air pollution (CO_2 ton per capita) the arch is 1965–2009 while for water pollution (demand biochemical oxygen seasonally kilograms per day per person) is 1994–2005. Furthermore, all three dependent variables are expressed in per capita.

[114]It is interesting to mention the fact that an inverse N-relation seems to exists between economic growth and atmosphere and water pollution. This peculiar shape of the curve confirms the existence of an EKC relation between environmental degradation and economic growth (given by the quadratic and cubic terms of GDP in the equation). The first part of the curve, characterize by a growth without environmental degradation could be justified since in the early stages of development there is an abundance of natural resources but economic sectors are not yet to a level of expansion such as to deplete them.

[115]Kt of oil equivalent per capita.

the variables.[116] Short-run results evidenced a negative impact on forest due to economic growth, population density, and energy consumption while trade did not impart deforestation. However, the negative effects of GDP, population and energy is diminishing in the long-run and this supports the existence of an EKC for deforestation in Pakistan.

The same approach of Ahmed *et al.* (2015) has been applied in the case of Indonesia by Waluyo and Terawaki (2016) over the period 1962–2007 supporting the existence of a reverse U-shape relationship between GDP per capita and deforestation in the long-run with a turning point of US$ 990.4. Recently Maji (2017) conducted a similar study even for Nigeria using agricultural land from 1981 to 2011 as a proxy to measure forest loss. Short- and long-run results demonstrate a positive effect of GDP and trade openness in reducing deforestation, conversely to population growth. Furthermore, the power to reduce deforestation for economic growth is stronger in the long-run supporting the second-half of the EKC curve.

1.4.3 The Brazilian Amazon rainforest

Among specific case studies focused on deforestation and economic growth, the Brazilian Amazon represents one of the most emblematic. In fact, Brazil hosts more than 60% of the whole Amazon rainforest[117] (Volpi, 2007) and around 30% of the world's forest area (Skole and Tucker, 1993) representing one of the most important biodiversity bucket on earth (Capobianco, 2001) but also one of the most threatened. Since 1960s the Amazon started to become a "release valve" for the growing population of the country and for the development of the North—the less developed area of the country—boosted by the military government[118] (Pfaff, 1997) and followed by the program of structural adjustments imposed by the International Monetary Fund (IMF) in 1982 which resulted in contrasting effects on the Amazon forest frontier (Young, 1997). However, even with the advent of democracy the Amazon continued to experience high rates of forest loss, especially in the early nineties during the *Plano Real* which spurred deforestation through agricultural credit.[119] In fact, the Amazon rainforest has always been seen as a means

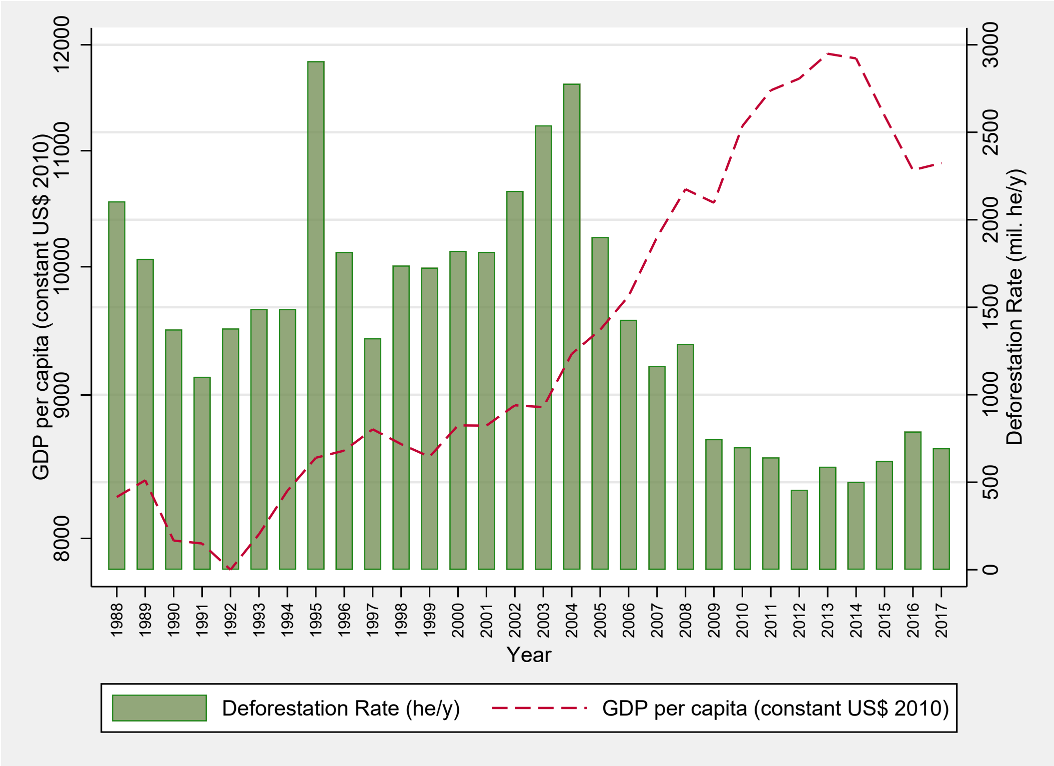
[116] Note that despite the model does not include the quadratic form of GDP, the ARDL estimation allows to study both the short and long run effect of the explanatory variables in exam.

[117] In Brazil the Legal Amazon is known as *Amazônia Legal* and it is composed by all the northern states of Brazil: Acre, Amàpá, Amazonas, Pará, Rondônia, Roraima, and Tocantins, plus parts of the states of Goias, Maranhão, and Mato Grosso.

[118] In charge from 1964 to 1985.

[119] Fearnside (2005) made a specific historical review of deforestation in the Brazilian Amazon.

Figure 1.16 *Brazilian Amazon, deforestation rates and GDP per capita (1988–2017)*



Sources: Author's personal elaboration based on data retrieved from INPE (2017) and WB (2017).

of development[120] for the North of Brazil and government policies which incentives clear-cutting committed to this common believe. Nevertheless, the boom-and-bust theory (Celentano *et al.*, 2012; Celentano and Verissimo, 2007) evidenced how deforestation frontier generates a parabolic pattern of human development' levels: "relative standards of living, literacy, and life expectancy increase as deforestation begins but then decline as the frontier evolves, so that pre- and post-frontier levels of human development are similarly low" (Rodrigues *et al.*, 2009)[p.1435]. However, recent works tend to confute the boom-and-bust path of human development in the Amazon (*e.g.* Tritsch and Arvor, 2016; Weinhold *et al.*, 2015).

Causes and drivers of deforestation in the Brazilian Amazon have been broadly assessed in literature. Major drivers during 1970s and 1980s could be found in the works of Fearnside (1982) and Pfaff (1997) while Volpi (2007) made a review of recent treats: cattle ranching and soybean productions (Nepstad *et al.*, 2006), illegal loggings (Nepstad *et al.*, 1999) and subsistence agricultures[121] (Alencar *et al.*, 2004; Fearnside,

[120]Even a Cost-Benefit Analysis of the economic value of the Brazilian rainforest has been conducted placing the value to 18,000 US$/he (prices at 1990) (Andersen, 1997).
[121]Made especially through slash-and-burn activities.

2005), forest fires (Cochrane, 2000), and the realization of infrastructures such as roads (Barber *et al.*, 2014) and hydroelectric power plants (Fearnside, 1988).[122]

Only in recent years deforestation rates in the Brazilian Amazon showed a remarkably slowdown starting from 2004, year of the implementation of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (*Plano de Acção para a Prevenção e o Controle do Desmatamento na Amazônia Legal*, PPCDAm) (Governo Federal do Brasil, 2004) as shown in Figure 1.16. PPCDAm program represented for sure a positive policy to prevent forest losses in the Amazon but other explanations are provided by recent literature such as technological improvements in agriculture (de Souza *et al.*, 2013), presence of protected areas (Barber *et al.*, 2014), or interventions in beef and soy supply chain (Nepstad *et al.*, 2014). However, despite this remarkable slowdown in deforestation rates, Richards *et al.* (2017) raised doubts about their truthfulness. In fact, the use of an official system (PRODES)[123] for controlling forest losses resulted in landowners which, aware of the monitoring system, avoid or shift deforestation in non monitored areas, for example in the Cerrado, the area just below the so-called arch of deforestation.[124]

Alongside deforestation rates provided by the satellite monitoring project PRODES, also GDP per capita of Brazil is reported in Figure 1.16. Empirical evidence suggests for a possible existence of and inverse U-shape relation between economic growth and forest Amazon depletion in Brazil. This evidence has been verified by Polomé and Trotignon (2016) through a cointegration approach applied to historical trends of deforestation and GDP per capita from 1975 to 2014[125] stressing the weighty role played by the Action Plan of 2004 and identifying a turning point at US$ 6,200–6,300 that could be potentially reached after 2020. However, considering current trends in Brazilian GDP growth and a new increase in deforestation rates, this prediction seems to be unachievable.

[122] The hydroelectric power plants of Balbina in the state of Amazonas (Fearnside, 1989) and Tucuruí in the state of Pará (Fearnside, 2001) represent two major historical cases. Moreover, the controversial Belo Monte project is a new possible vehicle of both development and deforestation for the Amazon which generated—and still does—an huge debate also in literature (*e.g.* Fearnside, 2006; Magalhães *et al.*, 2009; Reid *et al.*, 2010; de Castro *et al.*, 2011; Santos *et al.*, 2012). However, several new dam projects are planned in the future of the Brazilian Amazon (Tundisi *et al.*, 2014).

[123] Satellite monitoring of the Brazilian Amazon rainforest (*Monitoramento da Floresta Amazônica Brasileira por Satélite)* (INPE, 2017).

[124] Located in the Southeast of Legal Amazon.

[125] Authors used PRODES data (INPE, 2017) for the period 1988–2014 and made a reconstruction for the previous period using data from Fearnside (1982), Skole and Tucker (1993), and Andersen *et al.* (2002).

Notwithstanding, GDP data used by Polomé and Trotignon (2016) refers to the whole Brazil while deforestation in the Amazon expands only in the North region of the country which is also the poorest.[126] Although the economic growth of Brazil undoubtedly affects the Amazon region in both negative (depletion of natural resources from the North with displacement of benefits in the South) and positive (adoption of forestry policies at national level specifically focused for the North region) prospectives, it would be wiser to investigate only the economic growth of the Amazon region. In this regard it is worth mentioning the work of Araujo *et al.* (2009) which investigated the EKC for the Brazilian Amazon at State-level for the period 1988–2000 posing a particular attention to property rights' insecurity. Through a Two-Stages Least Square (2SLS) (Baltagi, 2013) analysis of their panel data, the evidence for an EKCd at state level results to be weak. Furthermore, insecure property rights is proven to be a major driver of deforestation alongside population density and presence of roads.

Going further in the Amazon topic, Oliveira and Almeida (2010) deepened the analysis pushing forward into a municipality-level study of the EKCd. Collecting data from 2000 to 2006 for 782 municipalities the authors conducted a Geographically Weighted Regression (GWR) (Brunsdon *et al.*, 1996) able to catch the high spatial heterogeneity of the Brazilian deforestation phenomenon. Results show how all kind of curves[127] between economic growth and deforestation could be found in this region meaning how this relation is primarily a local issue. Furthermore, other explanatory variable used in the analysis showed how the amount of cattle, soy, and sugar cane alongside extraction of timber products, and the amount of previous forest area have an important spatial variability.[128]

Spatial econometric studies now are becoming increasingly common in literature (*e.g.* Baltagi, 2013) and their application to panel data represent a useful tool for policy makers since they help to localize proper forest policies. For example, as asserted by Oliveira and Almeida (2010), areas where deforestation increase with economic growth require development policies able to foster economic activities which rise inhabitants' income and welfare without relapsing on natural forests.

[126] The *Atlas do Desenvolvimento Humano do Brasil* represents a useful tool to investigate differences among Brazilian States with the maximum level of disaggregation (municipalities) for 1991, 2000, and 2010 (UNDP, 2013).

[127] Here are listed the various kind of curves found: monotonically increasing function, monotonically decreasing function, U-shaped curve, inverted N-shaped curve, N-shaped curve, and inverted N-shaped curve.

[128] The works of Araujo *et al.* (2009) and Oliveira and Almeida (2010) have been considered within the meta-analysis of Choumert *et al.* (2013).

Several recent studies investigated the main causes of forest degradation in the Brazilian Amazon through spatial models and satellite data.

Andrade de Sa *et al.* (2015) performed a Dynamic Spatial Durban Model (DSDM) (Debarsy *et al.*, 2012) for 248 Minimum Comparable Areas (MCAs)[129] during the period 2001-2010. The authors investigated those who are the main drivers of deforestation for each MCA (main effects) such as the past amount of deforestation—which means that this is a persistent phenomenon—, the amount of cattle, GDP from agriculture, natural forest, and rainfall. Furthermore, neighbor MCAs' characteristics influence deforestation in any given MCA due to a spillover effects such as high rainfalls and large presence of primary forests which tend to reduce forest loss. By contrasts, MCAs close to deforestation frontier are surrounded by counties with elevated levels of deforestation, thus they are negatively affected as well. Indirect effects (global spillovers) are represented by the sum of the two previous categories which stresses the relevance of the amount of forest area and precipitations at global level. However, the implementation of the PPCDAm program in 2004 reversed these findings showing the relevance of this policy in reducing deforestation in MCAs distinguished by elevated agricultural activities by shifting forest depletion to relatively low agricultural-intensive MCAs through a leakage effects.[130] Population density does not have a significant impact among the three levels of impacts. Test for the existence of an EKC have been performed as a robustness check of the model. While no statistical significance has been found for linear and quadratic GDP in the direct effects, a reverse spatial EKC relation between GDP and deforestation seems to exist for local and global spillovers. This means that GDP of each MCA has an initial negative role on deforestation in close counties until a certain threshold where this relation reverses.

Jusys (2016) concentrates his analysis on 486 municipalities[131] for the year 2010[132] conducting another GWR. However, conversely to Oliveira and Almeida (2010), Jusys used an economic distance[133] rather than the classic Euclidean one and considered GDP and demographic variables as endogenous. In line with Andrade de Sa

[129] This municipality agglomerations is provided by the Brazilian Institute of Applied Economic Research (*Instituto de Pesquisa Econômica Aplicada*, IPEA).

[130] "In other words, a high level of percentage of agricultural GDP (or rainfall) in a MCA helps to reduce deforestation in this MCA (direct effect), but at the same time it leads to an increase in deforestation in all other MCAs (global spillovers)" (Andrade de Sa *et al.*, 2015)[p.17].

[131] Municipalities with a forest cover area below 5% of the territory have been omitted.

[132] Although the work keeps out the time evolution of variables, the use of this year is particularly useful for data availability due to census.

[133] Measured by travel time with Google.

et al. (2015) previous work, Jusys's work concluded for the existence of a U-shape relation between GDP and deforestation with a break-even point at 3,570 R$/month,[134] thus the opposite of the EKC curve. The use of a great amount of other explanatory variables enriched the analysis by giving an interesting pattern of the main drivers of deforestation and how they change across the Amazon region. Cattle ranching boosts deforestation in all regions of the Legal Amazon. Crop cultivations concur to deforestation only in the area between the states of Mato Grosso and Pará, in the lower area of the Amazon, while in the northeast of Pará the relation is opposite since there crop productions tend to replace previous grazing areas. This remote area, together with the northwestern states of Amazonas and Roraima, is where roads networks incentive deforestation the most. Differently, in the middle and south of Pará the presence of roads has a feeble effect since they have already played their role in the past.[135] Other drivers have been identified in timber value while altitude, constrain in rural credit, precipitations, and presence of protected areas tend to slowdown deforestation.

Another noteworthy analysis in the group of spatial econometrics works focused on the Brazilian Amazon is the recent research conducted by Faria and Almeida (2016) which investigated the role of international trade and economic growth between 2000 and 2010 for 732 municipalities but without testing for a possible EKC. Results show how trade openness increases deforestation in the area as well as soybeans and cattle production, and insecure property rights. Furthermore, the presence of protected areas tends to reduce forest losses and even economic growth seems to have a positive role too.[136]

Although some of these works confute the existence of a EKCd for the Brazilian Amazon at local level, Tritsch and Arvor (2016) are not of the same advice. Inspired by Rodrigues *et al.* (2009), they realized a database of environmental and socio-economic indicators projected a grid of more than 30,000 cells, each of 100 km^2, for the years 2000 and 2010.[137] Afterwards, cells have been classified, based on both

[134] Equivalent to US$ 2,030 considering the official exchange rate of 1.76 (LCU per US$, period average) for 2010 (WB, 2017).

[135] For example, the Trans-Amazonian Railway, which bisects the Brazilian Amazon from East to West, has been started in the seventies and crosses the center of the state of Pará and the southern border of the state of Amazonas.

[136] Other recent works in spatial interactions for the Brazilian Amazon faced several aspect such as Richards *et al.* (2014) which investigated the relation between agricultural sector and land use change, Amin *et al.* (2015) the role of protected areas, and Brown *et al.* (2016) land occupation.

[137] The use of a specific grid is justified by the fact that census sectors increased abruptly in the Amazon between the two years, thus they are not suitable to investigate the specific phenomena of deforestation of this area.

deforestation extend and activity, in seven frontier classes following the classification of Rodrigues *et al.* (2009).[138] Authors provide a new confutation of the boom-and-bust theory concluding for the existence of the EKC meaning that socio-economic[139] growth is no longer a driver of deforestation. Albeit this work does not follow previous methodologies for spatial econometrics, it used data coming from the same sources and the level of disaggregation is elevated making it possible to enumerate this study in the same plethora.

This brief review of those who are the main drivers of deforestation in one of the biggest and threatened forest worldwide highlight how multiple factors compete in determining forest losses. A bird's eye glance at data seems to suggest a possible existence for an inverse U-shape relation between deforestation and economic growth for Brazil. However, Amazon Rainforest is only a part of the story because Brazil is composed by six different biomes and the Amazon—albeit the largest—is only one of them,[140] thus the question should be broadened to the entire country. Unfortunately, forest data for the rest of Brazil are not accurate as much as for the Amazon region (FAO, 2014). According to literature, the EKC for the Amazon seems to be verified for high level of aggregation, yet moving to a more disaggregated level of analysis previous findings soon become weaker if not confuted.[141] These conclusions, even if still debated, seems to define the EKC for deforestation as a macro-level effect instead of micro/local-level validating the idea of List and Gallet (1999) that more disaggregated analysis characterized by similar individuals could lead to different results.

1.5 The Forest Transition hypothesis

The debate around the importance of the environment flourished at the beginning of the nineties increasing the worldwide attention to forests, especially for tropical developing countries, and one of the main theoretical results has been the *Forest Transition* hypothesis, first proposed by Mather (1992). It is curious the fact that this

[138] Classes span from A to G, where A and B (pre-frontier) are characterized by low level of deforestation extend and activity. In C, D, and E deforested area and deforestation activity increase (active frontier). Finally, classes F and G (post-frontier) is where deforested area is elevated while deforestation activity is low.

[139] Authors considered not only income per household but also literacy rate and access to basic services (*e.g.* sanitation).

[140] Starting from the largest: Amazônia, Cerrado, Meta Atlantica, Caatinga, Pampa, and Pantanal (IBGE, 2004).

[141] Results from the works of Polomé and Trotignon (2016), Araujo *et al.* (2009), and Oliveira and Almeida (2010) could confirm this conclusion.

theory was born at the same time of the EKC resulting in a highly conceptual and graphical analogy between them. This intuition derived from the observation of historical trend of forest cover for developed countries which experienced first a decrease in forest cover followed by a return in forest growth, thus a transition from "old growth" forest to "second growth" and planted forests as suggested by Sedjo (1987).[142] Accordingly, Mather (1992) posed the following questions: "if an areal transition has taken place in much of the developed world, may it be expected also to occur in the tropics? Are current trends in tropical deforestation likely to continue indefinitely into the future, or should they be regarded simply as temporary phases that will (soon?) give way to stability or expansion?" [p.367].

Despite the lack of reliability and comprehensiveness of forest cover data for long period over time, some evidences from developed countries offer a clearly support for this transition. For example, after 1650 France evidenced an increase in forest cover loss.In fact, in 1990 the volume of forests was more than 70% larger than the level of the French Revolution, almost equal to the level of the mid 17^{th} century. Hungary, just like France, experienced substantial forest expansions during the last 100 years (Mather, 1992). Furthermore, first evidences of the FT have been proposed for 12 countries during the last century by Walker (1993).[143]

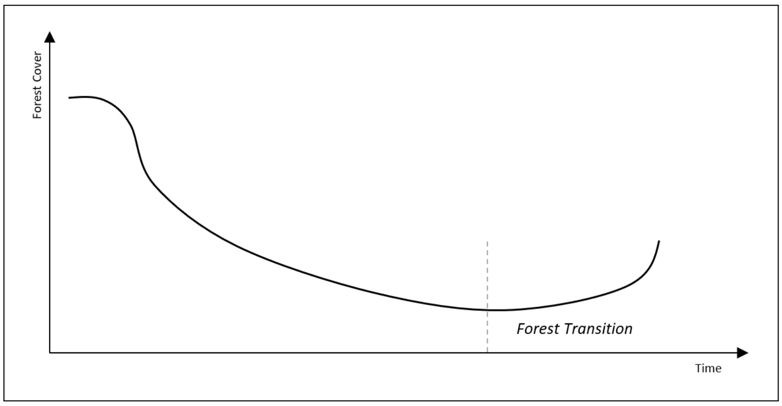
However, each country experienced the transition path in different ways, with different times and intensity. Mather (1992) showed how the decrease in forest cover for France and Great Britain has been spreader along time compared to United States where it has been more recent and abrupt but with a remarkable level of remaining forest before the transition occurred.[144] Moreover, after these groundbreaking studies which first proposed the FT, a great amount of works investigated the possible existence of the transition, first for developed and then—especially recently—for developing countries (*e.g.* Rudel *et al.*, 2005; Pfaff and Walker, 2010; Meyfroidt and Lambin, 2011; Hosonuma *et al.*, 2012; Wolfersberger *et al.*, 2015). Notwithstanding, the FT phenomena has been mainly developed and explicated by social scientists and geographers, but now a growing economics literature started to embrace, investigate, and modeling this theory and a proper review is proposed by Barbier *et al.* (2017).

[142] Mather (1992) mentioned the following statement of Sedjo (1986) to introduce the FT: "forestry today is experiencing a transition similar to that which occurred in agriculture much earlier in history" [p.5].

[143] The author evidenced a transition for the following states: Canada, France, Greece, Italy, Japan, Norway, Portugal, Puerto Rico, Spain, Switzerland, United Kingdom, and United States.

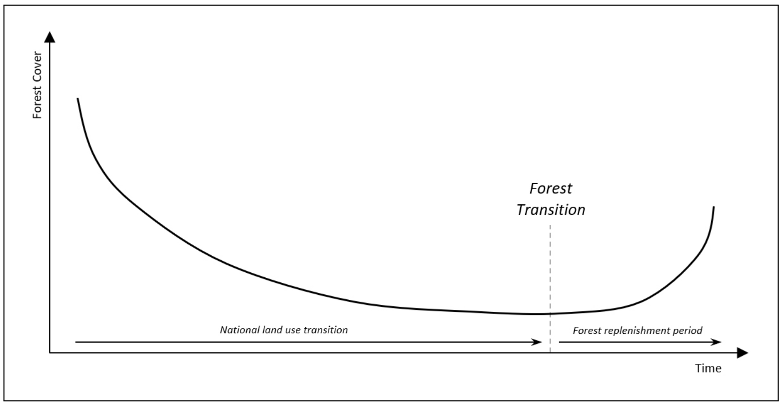
[144] In Britain and Ireland the native forest almost disappeared entirely before the occurring of the transition (Mather, 1992).

Figure 1.17 *The forest transition*



Source: Author's personal elaboration based on Grainger (1995).

Figure 1.18 *Revised forest transition*



Note: Unified model combining the national land use transition, forest transition, and the forest replenishment period.
Source: Author's personal elaboration based on Grainger (1995).

Graphically the FT starts from the resource depletion-melioration model of Whitaker (1940)[145] and the original proposition of Mather (1992) is presented in Figure 1.17. Grainger (1995) proposed a modified FT considering the Mather's original model within a broader perspective alongside the national land use transition process. In fact, while Mather recognized the fact that there could be a delay before the beginning of the transition after the end of depletion, this possibility was not explicated. This delay is justified by Grainger (1995) who explained how this occurs because the turning point could be achieved only when the national land use transition has ended, and even when it occurred the forest transition does not necessarily

[145]This model states that natural resources first are depleted and then renewed but with a level lower than the initial resource extent. The fact that natural resources do not reach the initial level during the re-growth phase is present even in the FT.

follows immediately.[146] Therefore, the bottom threshold of the FT, thus the period between the end of the national land use transition and the beginning of the forest replenishment period, evinces a remarkable flat period of delay as showed in Figure 1.18.

The occurrence of the FT has been explained by different determinants. The first proposition of Mather (1992) is mainly focused on the role of population growth and urbanization as main driving force. Rapid population growth is commonly associated with a fast depletion of forest while a slowdown with an expanding forest cover. However, rates of deforestation and population growth do not follow the same way at the same time. Another explication, provided by Mather and Needle (1998), focused on the increasing agricultural adjustment to land quality through a process of learning by doing of the farmers. This process is divided into three phases: the transition from phase 0 to phase 1 is accompanied by a degradation in forest cover; afterwards, farmers learn to distinguish between land with different quality and then, from phase 2 to phase 3, they move their activities only on higher quality land leaving others that could reconvert eventually to forest. In this perspective, Wolfersberger *et al.* (2015) and Barbier *et al.* (2017) proposed two economic models of competing land value use to determine when the transition occurs. Grainger (1995) differentiated between a normative and a critical transition. The former is characterized by some ideal conditions such as investment in agriculture able to rise the productivity on high quality land—and offset the effect of increasing population—and protection for remaining forests provided by the government. The latter is more realistic, where a less level of optimal conditions leads to a higher depletion of forests, thus a more sunken bottom level of the FT curve. Even Rudel *et al.* (2005) evidenced two kinds of FTs apart from agricultural expansion which could even overlap each other. In some places economic development increase the opportunity cost of work outside the farm sector by reducing consequently the agriculture area which revert to forests, also named *economic development path*. In other places, the scarcity of forest products could spur private landowners and the government to carry out projects of forest plantations in order to sustain the supply of these products, and named *forest scarcity path*, instead.

[146]In some countries, like US, when the delay has been relatively short (few decades), it has also coincided with the end of the national land use transition. Conversely, in other countries, like United Kingdom, the transition could be relatively delayed (Grainger, 1995).

1.5.1 The FT as upside down of the EKC

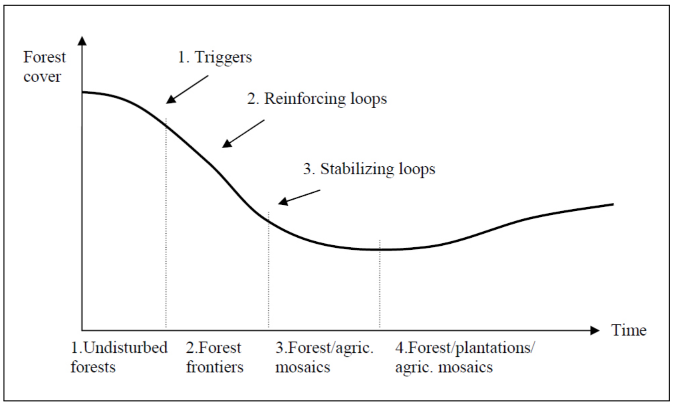
The FT remarkably resembles the EKCd—or rather a reverse version—for its U-form and the FDP could be easily associated to it as well remarking how these theories are highly interrelated each other. In the early stage of the FT is associated the beginning of the EKCd, a pre-industrial country, and the first phase of the FDP. The increase in forest cover loss occurs when the forest value function increases in the second phase of the FDP and open access natural forests are depleted the most. The steeper left-side of the EKCd with the development of heavy industrial sectors occurs in this phase of the FT. Finally, the third stage of the FDP begins during the lower bound of the FT, and this curve starts to rise when the EKCd's turning point has been overcome.

Linkages and differences between FDP, FT, and EKC could be found at first in the work of Angelsen (2007) which attempted to combine the von Thünen's model with the FT hypothesis. He divided the FT into four phases as showed in Figure 1.19 and proposed, for each one of them, the corresponding changes in agriculture and forest rents as showed in Figure 1.20. In the first phase of undisturbed forest, agricultural value rents are low and the conversion of forest land is scant. In the second phase, characterized by triggers and reinforcing loops, agricultural value rises and forest cover is depleted. Triggers characterize the period between the first two phases and the most important of them are the construction of roads which spur rent seeking activities creating new market opportunities and inducing technological changes. Subsequently, reinforcing loops occur, such as economic development and population growth, and they rise agricultural land rents by reducing the cost of agricultural inputs and transports but increasing the price of outputs. Consequently, these loops could stabilize and for example economic growth could lead to more profitable work opportunities outside agricultural and forestry sectors reducing the value of the agriculture function—the economic development path. Eventually, the scarcity of forest products shift upward the curve of forest rents fostering plantations and better forest management able to restore the forest cover—the forest scarcity path.[147]

Following Mather *et al.* (1999), Angelsen (2007) recognized the undoubted similarity between FT and EKC hypothesis, beware to not equate these two ideas for

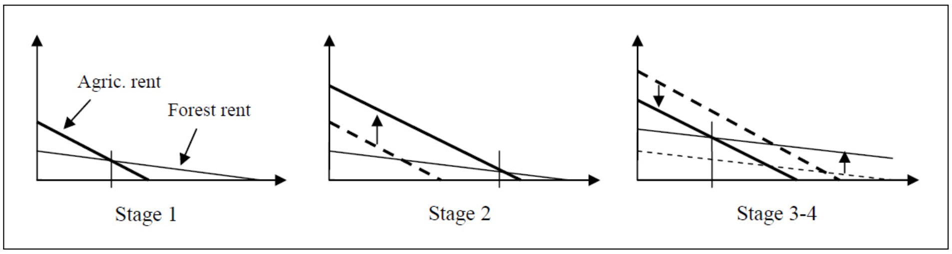
[147] Angelsen (2007)'s proposition is quite similar to the one proposed by Hyde (2012) but some differences are noteworthy. First, since the FDP always refers to the forest frontier, in this case it begins by starting from the second phase of Angelsen. Second, the basic FDP does not contemplate a shift downward of the agricultural value function. Third, the curve of the cost for securing property rights is absent here.

Figure 1.19 *The stages and main drivers in the forest transition*



Source: Angelsen (2007)[p.32].

Figure 1.20 *Changes in agricultural and forest rent curves during the forest transition*



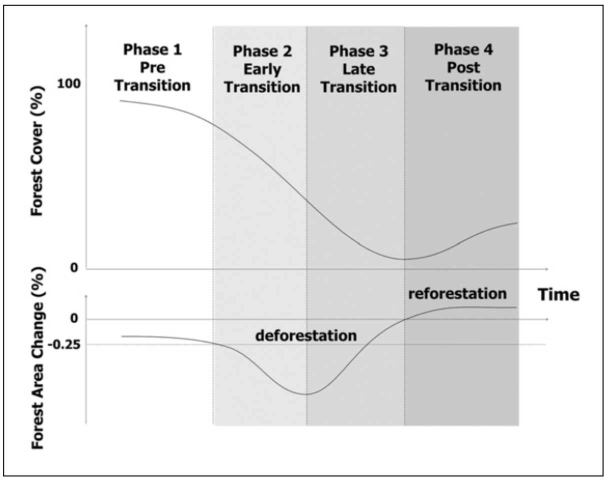
Source: Angelsen (2007)[p.33].

three main reasons. First, the different x-axis between the two models. Second, the implication of high deforestation rates in the initial phases of the EKC, too strong for the FT. Third, the unnecessary reforestation period in the EKC. Nevertheless, these assumptions do not seem to be insurmountable. In fact, assuming a continuum positive economic growth for a country, the x-axis of the EKC could be substituted by the time while the environmental degradation on the y-axis could be substituted by a change in forest cover—thus a vertical flip of the reverse U-shape curve—and the result would be a potential FT curve.[148] Moreover, some graphical representations (see Figure 1.9) of the EKC assume low rates of environmental degradation at the beginning of development and this is probably particular valid for forest use as well. The third assumption is probably the weaker since the right-side of the EKC could be justified even by forest plantation and reforestation and not only by the same natural restoration—and Hyde (2012) stressed in particular on this point.

In the literature other two examples pose on the horizontal axis time and economic development interchangeably. Redo *et al.* (2012) used the HDI as development

[148] Some problematic in that sense could occur, considering the modified FT proposed by Grainger (1995), when the transition takes time to occurs. However, the time-growth translation would be justified in a stagnation or low growth levels.

Figure 1.21 *Four phases of the FT model*



Source: Hosonuma *et al.* (2012)[p.2].

proxy on the horizontal axis of the FT. Instead Hosonuma *et al.* (2012) suggested four phases—not to be confused with those proposed by Angelsen (2007)—of transitions along a reverse J-shape FT curve: pre-, early, late, and post-transition as showed in Figure 1.21. Furthermore, even an upside down view of the FT and the curve for deforestation is proposed despite non directly identified as a (reverse) Kuznets curve.

Eventually, a final "bad" simplification equates the EKC with the FT, the fact that they were often seen as automatic process which promise to solve environmental problems without any policy intervention (Rudel *et al.*, 2005). The former with simply economic growth, the latter with time, both with no regards for the respective x-axis, or rather the level of deforestation and forest loss. Conversely, despite criticisms, these are both models with the aim to help policy maker to address environmental problems and not a justification to prevent government interventions.

1.6 A joint view of three theories: EKC, FT, and FDP

Along the three phases of the FDP, the curve of forest value shifts to higher values competing with agriculture. In the first phase, forest land's value is still low and shifting cultivation slowly move the curve upward. Therefore, economic and population growth of the country continue in the second phase where industries start to support the economy and the demand of forest products increases as well eliciting the forest frontier to deplete natural forest. In the third phase, the value of forest land increases again competing with agriculture for management forest areas, thus pressure on natural forest decrease and total forest area tends eventually to rise again. This forest development path could be simplified and presented through the famous EKCd exemplified in the upper graph in Figure 1.22. At the same time, a second graph could be added at the bottom of the previous representing the FT path *vis-à-vis* with the EKCd and both connected through the three-phase-model of the FDP. Here, the EKC starts from an approximately zero (or remarkably low) level of economic growth, thus a country at its initial level of development, with low levels of forest degradation corresponding to an approximately untouched forest cover when $t = 0$ in the FT. From this point moving forward, the two curves proceed along their paths assuming a continuous economic growth (increasing levels of GDP per capita) during time.

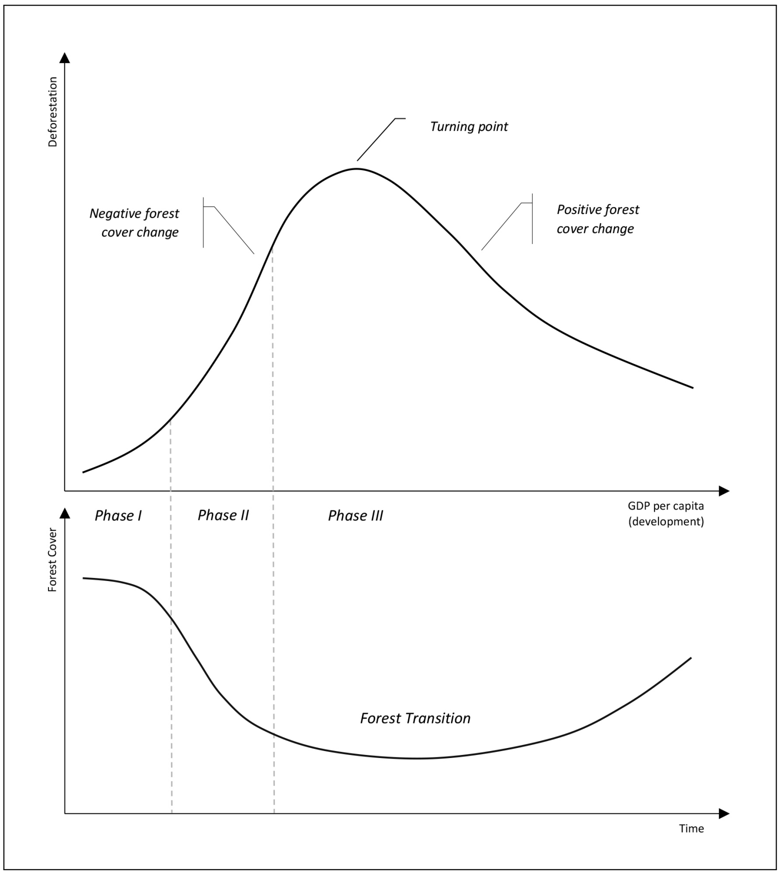
The first two phases of the FDP could be placed in the first-half of the two curves. The switch between phase I and II could occur when the rate of forest depletion starts to increase with higher rates, thus when the left-side of the curve becomes steeper and the loss in forest cover grows faster. Shifting from phase II to phase III the turning point in both curves could be potentially reached and the country could then follow a path characterized by economic growth and forest recover/increase abreast. The third phase of the FDP model is located at the top of the curve, approximately around the inflection point of the EKCd, thus when the rate of forest depletion starts to decrease.[149] In fact, with the advent of the third phase, managed growing forest areas start to appear and compete with products retrieved from open access natural forests land (as well as with agricultural area). However, the offset of harvesting forest rates is not an immediate result of this phase, conversely it requires time to occurs. Therefore, it is reasonable to identify the third phase of the FDP before the turning point of the EKCd and the beginning of the flat-bottom part of the FT. Eventually, when the two opposite turning points are overtaken the country enters into a phase of positive growing forest change. It could be identified even as an additional phase IV of *forest cover restoration* which proceeds on the right-side of the two graphs.[150]

In light of skepticisms raised by Angelsen (2007) in studying these two theories jointly, some clarification is required. First, it is not completely true that the EKC assumes elevated levels of deforestation rates at its beginning. This is due only to its mathematical construction and because it is not possible to investigate the

[149] However, the EKC is not strictly defined and several shapes have been presented in literature. The idea of some inflection points where to locate the FDP's phases it is just an approximation.

[150] The possibility to add a fourth phase to Hyde's FDP has been proposed by G. A. Navarro (personal communication, November 9, 2017).

Figure 1.22 *EKC for deforestation, FT, and FDP: a first version*



Source: Author's personal elaboration.

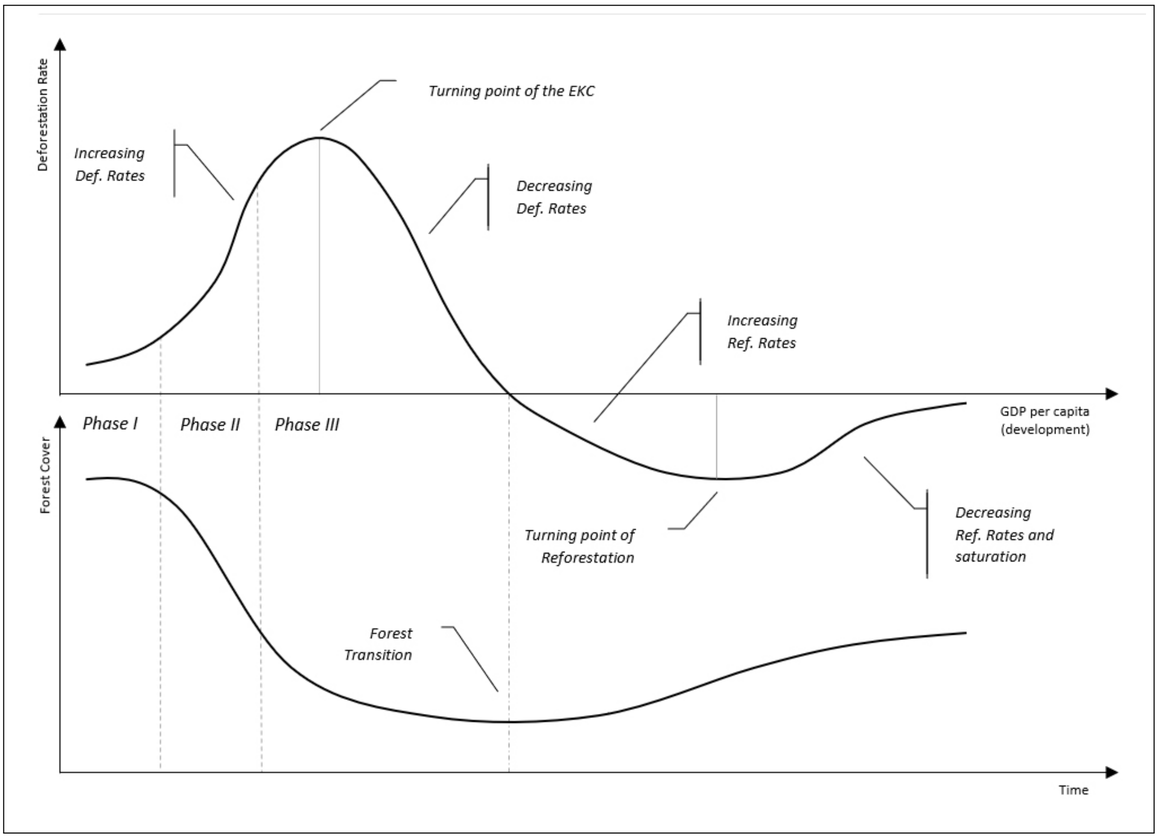
initial left-side of the curve as explained in Section 1.3.3. Second, it seems hard to not consider reforestation processes in achieving the EKCd, especially if total forest cover—as it is usually done in this literature—is used to investigate the phenomenon. In fact, increasing management forests allow to slowdown the degradation of natural forests and an economic development would eventually lead to an increase in forest preservation for non consumptive use and forest erosion control.[151]

It must be noticed the fact that Figure 1.22 represents a slightly different EKC to what is effectively presented in literature.[152] In fact, the curve assumed a level of zero deforestation at its peak, shifting from a negative to a positive forest cover change. This exemplification allows to locate the upper threshold of the EKCd approximately in correspondence with the bottom level of the FT where forest cover

[151]The point raised by Angelsen (2007) would be true if only natural forest is considered in the assessment of the EKC. However, even if only this type of forest is considered it would follow the FT path as well as graphically showed in Barbier *et al.* (2017).

[152]Nevertheless, Culas (2012) proposed a similar graphical version of the EKCd.

Figure 1.23 *EKC for deforestation, FT, and FDP: a second version*



Source: Author's personal elaboration.

start to growth again. With this first version, the FT curve could be seen effectively as a reflection of the EKCd assuming a continuous economic growth during time. Alternatively, this EKC could be interpreted as the cumulative loss of forest cover which first increase and then, reaching the turning point of the FT, starts do decrease due to the regrowth phase—which slowly overthrow previous losses.

However, usually the y-axis of the EKC represents levels of environmental degradation—in this case deforestation rates or a negative forest cover change—, hence a more appropriate view of the joint representation of EKC, FDP, and FT would be similar to the one presented in Figure 1.23. Here the EKC follows its "natural" path and, compared to the previous version, it would be shifted on the left. Therefore, when the level of degradation ends (deforestation rates), at this point, in correspondence with the occurrence of the FT, the curve should presumably continues through the half-plane below during the reforestation period (negative deforestation rates or positive reforestation rates). Obviously, this representation would change according to the variable used to express the deforestation-reforestation process or to account for forest cover variable.[153] Giving a more accurate look a this graph, assuming the curve of the FT as a function of forest cover ($f(x)$), the curve of deforestation substantially is its the negative first derivative ($-f'(x)$). For this derivative it could be assumed a smooth initial phase corresponding to the beginning of the FDP where the depletion of natural forest is not highly intensive. The first inflection point of $f(x)$ corresponds to the turning point of the EKC while at its flat point is when the derivative reach the level of zero deforestation to continue in the phase of restoration. However, this EKC could reasonably show another turning point, less pronounced than the first one, which represents the highest level for reforestation rates. In fact, as well as is impossible to imagine an infinite level of deforestation (which necessarily ends when forests are completed depleted), so the reforestation process cannot continue indefinitely but after reaching the minimal value of $-f'(x)$, slowly diminishing with an asymptotic behavior. This proposed curve is particular different from those commonly observed in literature since it is enriched by a second (negative) section which is not the "classic" N-shape curve because the second side of this EKCd occurs in a phase of reforestation, or rather environmental restoration.[154] This "kind" of N-shape curve is not investigated in the common literature since is impossible to have a restoration in terms, for example, of CO_2, even because the tendency for this pollutant is to increase with GDP or declining in a non-overly hinted way. Otherwise, the variables used for the EKCd, deforestation rates or changes in forest cover, can effectively move from a negative to a positive interpretation.

Hyde (2012) proposed an interesting theoretical analysis of the EKC for deforestation throughout the three stages of the FDP. His main attention is rightly focused on the pattern of forest products' demand as income rises: consumptive and non-

[153]The forest coverage of a country is reasonably different from the whole tree coverage. In fact, while a forest to be designate as such requires specific canopy density—and definitions change among states—in the broad category of tree forest all shrubs are considered, even those on the roadsides or backyards. Therefore, a curve which uses this variable would be presumably shifted on the left compared to the one with the use of a forest cover measure. However, in this category would be counted even plantations such as palm oil which have a truly low biological contribution. Furthermore, in Indonesia and Malaysia, where is locate the major production of palm oil, the expansions of these plantations occurred even to the detriment of natural forests raising a global concern and debate about the issue (*e.g.* Fitzherbert *et al.*, 2008; Koh and Wilcove, 2008).

Another interesting curve to assess in this perspective would be the one of captured CO_2 from forests. In this case the curve and its turning point would be shifted on the right compared to the one for deforestation rates since the amount of CO_2 that could be stored by regenerated or secondary forests is low compared to primary natural forests. Furthermore, even after the occurrence of the FT, natural forests could continue to show a decrease, whereby the amount of uncaptured CO_2 from these forests would require more time to be filled by the storing capacity fo new forests.

[154]Obviously, it is not to be excluded the fact that an N-shape with a return in deforestation with higher GDP levels but it should be interpreted as a temporary fluctuation along the suggested FT.

consumptive demands for wood and forest-based environmental services,[155] and the competing use of land between agriculture and forests. The demand of primary consumable forest products (such as fuelwood, sawnwood for lumber, industrial roundwood, plywood, and papers) tend to decline as income rises due to a negative income elasticity.[156] Conversely, primary non-consumable forest-based activities (such as recreation and ecosystems services) tend to increase with income due to a positive income elasticity.[157] Furthermore, even forest for erosion control, planted by governments and landowners in any stage of development, will be allegedly fostered with improved institutions and economic development. Lastly, concerning agricultural land, despite growing population in developing countries, its use declines over time with economic growth due to a positive but small income elasticity. In conclusion, Hyde (2012)[p.241-242] affirms:

> We can reasonably speculate that, with development, the demands for the management and protection of forests and trees eventually exceed both the demand to harvest them and the demands to convert the forestland to agriculture use. This conclusion is consistent with an EKC for forestry. [...] Thus, knowledge of the income elasticities for forest products and observations of the three-stage pattern of forest development are two reasons to accept th EKC hypothesis that economies in the early stages of development deplete their trees and forests but, as development proceed and incomes rise, relative values shift, and the forest recovers.

These theoretical conclusions have not been effectively verified in the vast EKC literature where forests occupy a relative modest role compared to other environmental variables. In fact, Jordan (2010) pointed out how among 255 articles and 373 observations above the EKC, deforestation holds only a modest 8%. Therefore, the meta-analysis of Choumert *et al.* (2013) albeit evidenced a decrease in consensus for this peculiar EKC considers this theory definitely not over. Indeed, Hyde (2014) stressed how the possible existence of an EKC for deforestation still represent one of the twelve unresolved questions for forest economics.

1.6.1 A flattened EKC for deforestation through the FDP

In the same ways chances of a flatter EKC has been proposed by some authors (*e.g.* Panayotou, 1993; Munasinghe, 1999; Dasgupta *et al.*, 2002; Culas, 2012), the

[155] In this category are included trees and forests that are usually not included in national inventories.
[156] Buongiorno *et al.* (2003) evidenced this tendency.
[157] Hyde (2012) is confident with this conclusion despite the lack of a comprehensive summary.

same could be done for the FDP—and accordingly for the EKCd. In fact, shifting the problem of how to smoothen the EKC's shape-bell into the FDP, the aim of the policy maker would be to reduce the area of degraded open access forests. Hyde (2012) identified two fundamental means for minimizing the exploitation of this areas: reducing the cost of property rights and attracting human activities away from the degraded forest. The first point could be achieved by strengthening the role of property rights and institutions. Concerning the second point, the optimal way would be to offer better employment opportunity outside the forest sector. Both of these two goals are strictly related to a necessary development of the country. Figure 1.24 shows these two elements at work: less costly and better property rights shift downward the curve T_r while higher opportunity cost of labor makes the forest's value function steeper. These two combined improvements enlarge the extensive and intensive margin of management forests and reduce the third margin at the end of the degraded forest area. The result is a contraction of the open access area from $B_1''D_1$ to $B_2'D_2$ followed by an increase in the density and volume of forest in the remaining open access degraded forest area.[158]

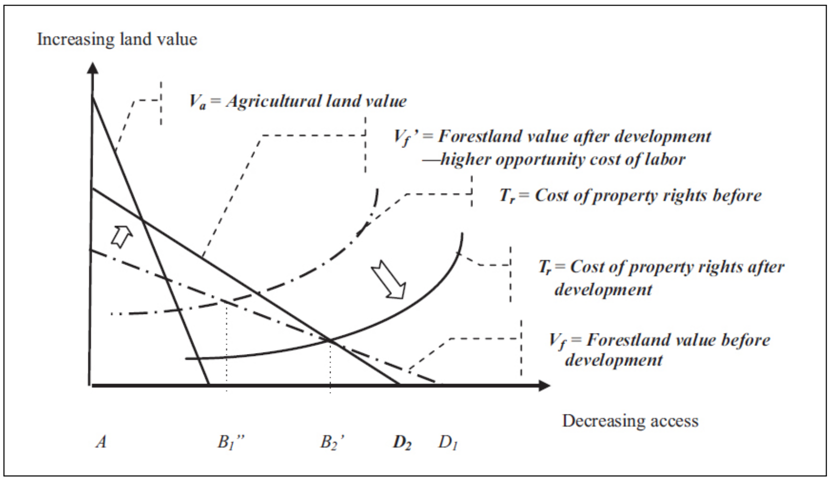
What is presented here is substantially the final stage of phase III, when the FD occurs and forest cover starts to grow again. This is what presumably can occur within the phase IV of the FDP following the quadruple subdivision of the FT curve proposed by Angelsen (2007). This final example represents also the end of this theoretical reassessment of the EKC which went through the various phases of the FDP and the path of the FT landing to an optimistic ending. However, this conceivable path would be only an illusion—or worse, a damnation—if it were considered as inevitable and automatic without an enhancing role of individuals, private sectors, and public interventions.

1.7 Concluding remarks

In his book *Deforesting the Earth: From Prehistory to Global Crisis, an Abridgment*, retracing deforestation's history Williams (2003) evidences how humans in 10,000 years had an "effect on global vegetation only slightly less dramatic and widespread than that of the Ice Age in the 100,000 years before" [p.11]. However, considering the worldwide growing population in developing countries—mainly located in tropical

[158]The area of managed forest could be enlarged even from some agricultural technological improvements which modify the curve of agricultural land value V_a making it steeper; for example, land-saving technological changes. However, different technological agricultural changes are able of both enlarge and reduce the area of managed forest as showed in Hyde (2012).

Figure 1.24 *Sustainable forestry and the control of deforestation*



Source: Hyde (2012)[p.166].

areas—which is supposed to stabilize around 9 or 10 billion by 2100, the impact on forest would continue unavoidably. Thus, the investigation of the evolutionary relation between societies and forests represents a necessary task and the EKCd, along the FT and the FDP, could be a useful means to carry out this analysis.

This chapter presented a comprehensive view of how first theories of land allocation could be used to explain both the EKCd and the FT under a unique theoretical background. Using the von Thünen's model, Hyde (2012) investigated land allocation among forest frontiers through three different phases of development. These could be retrieved along the two curves of the EKC and the FT, from the most high-depletion period until the two turning points when deforestation rates downtrend and eventually revert into reforestation and a return in forest cover.

Notwithstanding, theory alone is not sufficient to achieve opportune environmental policy implications. The EKC could represent a country-level tool—if properly addressed—to obtain useful feedback to transform into practice by policy makers. However, in order to do so, the first the question raised by Hyde (2014) requires an answer: EKC or not EKC? The answer will probably be not absolute and equal to all countries since different aspects are at stake. The following chapters will strive to bring clarity into this scattered literature with the purpose to obtain more robust conclusions and policy recommendations through a re-assessment of the EKC for the case of deforestation.

Eventually, considering all criticisms moved against the EKC, it would be a fair and useful reminder—before moving forward in the analysis—to quote that David

Pearce wrote[159] one week before he passed away in a survey about the link between growth and poverty: "[i]t hardly makes sense deliberately to inflict environmental damage on the poor just because this was the way the rich nations developed hundreds of years ago. There is no need to repeat that unhappy experience. In short, the EKC is neither inevitable, nor does it describe a desirable path of development" (IUCN, 2008)[p.30].

[159]These information, alongside the following quote, are provided in Johansson and Kriström (2007).

2 Historical trends in forest cover

When I reflect that one man, armed only with his own physical and moral resources, was able to cause this land of Canaan to spring from the wasteland, I am convinced that in spite of everything, humanity is admirable. But when I compute the unfailing greatness of spirit and the tenacity of benevolence that it must have taken to achieve this result, I am taken with an immense respect for that old and unlearned peasant who was able to complete a work worthy of God.

Jean Giono

IN retracing more than 100,000 years of deforestation, Williams (2003) concludes stressing the importance of history for forestry, just like for any other discipline. Unfortunately history is easily—or conveniently—forgotten and dismissed by policy makers with a more—if not unique—attention for the present. However, both the EKCd and the FT require a long time-span to be verified (or confute) and even in the very first work of Shafik and Bandyopadhyay (1992) this problem has been remarked. The previous chapter presented the EKCd's literature and its more recent developments and showed how total forest cover represents the core variable used to test this hypothesis. Therefore, this chapter attempts to "add more history" in the re-assessment of the EKCd suggesting a reconstruction of forest cover data that will be used in the following chapter to investigate the possible existence of the "famous" reverse U-shape relation between deforestation and economic growth.

The primary and more recent source of forest data is represented by the *Global Forest Resources Assessment 2015* of FAO which provides forest cover data divided into four categories: total forest, planted forest, other naturally regenerated forest, and primary forest, where the sum of the last two categories represents the so-called natural forest. However, FAO (2015) data covers only a relatively short period, from 1990 to 2015, and although it represents the more comprehensive source of forest data, it is all but critic-less. Nevertheless, the test of the EKCd, which will follow in the next chapter, poses primarily on this data source. Thus, this chapter aims to propose a reconstruction of the trend of forest cover for 114 countries, both developing and developed,[1] from the latest FRA 2015 to the first forest assessments made by FAO since its foundation in 1945. The reconstruction focuses on two categories of forests: natural forest and planted forest, which jointly represents the total forest cover. The category of primary forest has been left out and embedded in the one of natural forests since it has been recorded by FAO only recently. The reconstruction of the forest cover trend which will be presented has never been addressed in the literature. Although potentially affected by errors and flaws and undoubtedly characterized by a certain degree of subjectivity, this data could be truly useful in order to properly reassess the EKCd.

The following chapter proceeds as follows. The first section emphasizes the main difficulties related to forest data and explains the reasons for the choice of FRA 2015 data instead of other sources. The second section retraces a historical evolution of the forest assessments published by FAO since it has been the main comprehensive and consulted source of data. The last two sections of the chapter are focused first on the enlightenment of the methodology used for the reconstruction, then the specific reconstruction of total, natural, and planted forest trend conducted for each country.

2.1 Difficulties in dealing with forest cover data

It is a hard task to deal with forest data due to the biological differentiation of forests among latitude and altitude. Furthermore, each country tends to report forest cover data following various methodologies. Hyde (2012) stresses these problems showing how the definitions of forest differ widely across countries. The example given by the author is the one of Papua New Guinea, where the minimum area for forest classification is 10,000 times higher than the corresponding threshold for Czech Republic. Although FAO tends to make a strong effort to harmonize countries' FRA, Hyde (2012) recommends cautions in using this source for an international

[1]The division between developing (more precisely developing and emerging countries) and developed countries is the one provided by the IMF (2016)'s classification.

comparison. In fact, although FAO provides common guidelines to states, high differentiation among states' definitions and thresholds could affect the attainment of effectively comparable values. Since the first aim of the EKC hypothesis is to test its validity across countries and time, it is of pivotal importance to be aware of the handled data. Hyde (2012) suggests to avoid a cross-country comparison in forests psychical terms preferring instead the use of forest cover change or deforestation rates. However, national inventories do not always follow a fixed methodology among different editions. Definitions of forests and thresholds often change across time. Therefore, even if a comparison in forest change or deforestation rates is more suitable to overcome differentiations across countries, it is important to be aware of changes across time in order to have a comparability both across individuals and time. For example, India releases a forestry inventory called *The State of Forest Report* every two years since the first edition of 1987.[2] However, as showed by Grainger (2009), values of natural forest cover in 1990 reported by FRA 2000 and 2005 are different—17 million hectares higher—due to the reclassification of some plantations within the category of semi-natural forest. Furthermore, there is no differentiation between natural and total forest cover in the Indian inventories. China's forestry inventories represent another example. China published eight National Forest Inventory (NFI) since the first one in 1973-1976 but in the fifth edition (1999-2003) the standard of evaluation has been changed (Hyde, 2012; Zeng *et al.*, 2015).[3] However, conversely from India, China's inventories differentiate between natural forest and plantations.

There are various examples in the literature about problems related to deforestation's estimation and in general with the use of certain sources instead of others. Among others Myers (1980) and Allen and Barnes (1985) are two important works which empathize difficulties and limitations related to forest data. One of the main tricky matter in this compound is the one of forest definitions, namely different typologies of woodlands. In fact, the inclusion (or not) of some land categories instead of others[4] could change remarkably the effective "perception" of forest for a

[2]The last one, the fourteenth, has been released in 2015.

[3]For example, in order to overcome this problem avoiding cutting off some observations from their database, (Hyde *et al.*, 2008) used a simple dummy variable to differentiate between official data after and before the standard change.

[4]The category of shrubs is probably one of the most controversial within the forestry classification. Indeed, for some countries it represents a huge share of land. For example, Spain's forest cover data embodied shrubs for several FAO's FRA and it is not a case that the value for total forest in 1990 provided by FRA 1990 (FAO, 1995b) is around 50% higher than the same values provided by the latest FRA instead (FAO, 2015).

country. Moreover, if the inclusion (or not) of some categories of vegetation changes among different FRAs, this could affect the effective trend in forest cover. These problems are of main importance since they influence decisions in forest-oriented policies. Hyde (2012), using a great amount of practical examples stresses how a wrong or bad knowledge of the forest development path by policy makers could lead to bad policies whose results are null or negative.

As showed in the review of the literature, different authors used another FAO's source of forestry data named *FAO Production Yearbook* (FAO, 1995a) instead of FRA. There is a two-fold justification for this choice. First, the yearly availability of forest data, thus a long time series of forest cover, from 1960 up to 1994.[5] Second, the non-use of population growth to predict forest cover area, conversely to some editions of FRA. In fact, the value of forest cover in FAO Production Yearbooks is only the one reported by countries and it is not measured (Grainger, 2008). Although this alternative source of forest data could be seen as suitable for long-time cross-country comparisons, it embodies several limitations. First, Production Yearbook's data synthesizes under a unique forest category all kinds of wooded area without any kind of differentiation.[6] Second, the vast majority of data has been just linearly forecasted or interpolated between two different reported years. Third, since all data has been updated according to new reported data by countries, this source it is all but excused of some unrealistic values.[7] In the light of these limitations, FAO Production Yearbook is considered a less authoritative source of forest data (Grainger, 2008; Mather, 2005). Eventually, aware of the scant reliability of these forest data, FAO decided to end reporting these data in the Production Yearbooks.[8] However, even if the reporting of this data had been interrupted more than twenty years ago, they have continued to be used—especially in EKCd studies—for many years, even recently (*e.g.* Culas, 2012; Damette and Delacote, 2012; Busa, 2013).

[5]It is commonly used also the time span 1972–1994.

[6]The definition of forest and woodland of the Production Yearbook is the following: "land under natural or planted stands of trees, whether productive or not. This category includes land from which forests have been cleared but that will be reforested in the foreseeable future, but it excludes woodland or forest used only for recreation purposes" (FAO, 1995a)[p. viii].

[7]For example, Rudel and Roper (1997) pointed out the case of Nigeria where forest data for 1980 vary between one edition of the Yearbook to another without any explanation. This it is not an isolated case. In fact, consulting different volumes of this annual report it is possible to notice how data for the same year from different editions often suffer from this problem.

[8]This data has been made available by FAO through the AGROSTAT system, a diskette for PCs. However, nowadays it is not possible to retrieve this forest cover data on the web since the FAOSTAT database (FAO, 2017a) includes only FRA data. Therefore, the only feasible way—without the diskette—is to collect data directly from hard copies of this source. Unfortunately, each volume provides data only for 4 years with changes among different volumes.

In order to carry out the reconstruction of forest cover, FRA data has been chosen as a primary reference. Although several criticisms and weakness of this data have been raised by several authors (*e.g.* Mather, 2005; Grainger, 2008, 2009; Hansen *et al.*, 2013), they represent the source with the longest and largest coverage of forest data. FRA data is considered of poor reliability and characterized by difficulties in comparison among different assessments.[9] Some of these authors stress the higher reliability of satellite images instead of FAO's FRA; however, even this source is not error-free. It is possible to summarize this conflictive position by mentioning the words of MacDicken (2015)[p.4]:

> While the idea of long-term, high quality forest data collected using the same methods across time, forest type and countries with highly divergent access to technical and financial resources is attractive, it is also most impractical. At the same time, the assumption that remote sensing provides clear, accurate and precise results for forest change at the global scale is also tenuous. Recent attempts to report global forest change have made the mistake of characterizing tree cover change from satellite imagery as forest change (Harris *et al.*, 2012; Hansen *et al.*, 2013) without regard to the processes of natural regeneration and reforestation. Both of these studies have confused the distinction between forest and woody horticultural crops and as a result reflect tree canopy change, but not necessarily forest change.[10] Neither remote sensing nor country-based reporting provides perfect answers to forest resource change questions.

Thereafter, aware of the undoubted limitations of FRA data, a truly equivalent alternative is non existent (yet) essentially. An effective possible solution, suggested by Grainger (2008) would be a "wall-to-wall" survey using high resolution images.[11] However, the present work falls outside this possible solution since it would require a remarkable effort in terms of resources and time.

2.2 FAO's Forest Resources Assessment

Before moving over with the explanation of choices made for the reconstruction of forest cover trends, since FAO's FRA has been the main used source, an overview

[9]Grainger (2008) shows how results differ from 1980 to 1990 comparing values from different FRA. Furthermore, he compares also data referring to the same time span but using different sources (Grainger, 2009).

[10]For example, one critique to Hansen *et al.* (2013) has been moved by Tropek *et al.* (2014).

[11]Remote-sensing studies have been carried out since 1972 (Grainger, 2008). Thus, this proposal could be extended for an effective long time-span through an unique methodology, comparable across time and among countries.

of FRA's history is definitely necessary.[12] Furthermore, another historical review of FAO's FRA, from the beginning to 2000 has been made by Mather (2005). Instead, differences among FRAs since its 2005 edition could be found in Grainger (2009).

The first global forestry survey published by FAO dates back in 1948 with the name *Forest Resources of the World* (FAO, 1948). This report covered approximately 66% of the world total forest area. Subsequently, this source has been followed by the *World Forest Inventory 1953* (FAO, 1957) with a coverage of 73%. This value increased to 88% with the following *World Forest Inventory 1958* (FAO, 1960). Instead the *World Forest Inventory 1963* (FAO, 1963) has been characterized by a decrease in countries response due to the ongoing of independence processes in several developing countries.

During 1970s FAO published several regional forest assessments: the *Forest Resources in the European Region* (FAO, 1976c), the *Forest Resources in the Asia and Far-East Region* (FAO, 1976b), the *Appraisal of the Forest Resources in the Latin American Region* (FAO, 1976a), and the *Forest Resources of Africa—an approach to international forest resource appraisals*, divided into two parts (FAO, 1976d,e). Even though FAO did not conducted a global assessment during the seventies, a substitute review has been carried out by Persson (1974) with his *World Forest Resources. Review of the world's forest resources in the early 1970s*.[13]

FRA 1980 represents an important document for its breadth, covering 97% of developing countries' land. It is important to mention the fact that it has been the first assessment which used a quantitative definition of forest, with specific parameters.[14] Using expert opinions some adjustments in time have been made in order to allow comparison among previous data and projections. Furthermore, some interpretations of satellite images have been conducted in order to overcome some lacking information. This FRA is characterized by a main volume *Tropical Forest Resources* (Lanly, 1982) and by three specific regional assessments: Tropical Latin America (FAO, 1981a), Tropical Africa (FAO, 1981b,c), and Tropical Asia (FAO, 1981d). FRA 1980 has been followed by a global *Interim report on the state of forest resources in the developing countries* (FAO, 1988). In fact, this document provides data both for developing and industrialized countries even though the amount of information for the latter is quantitatively lower than the former. Moreover, it is

[12] In order to carry out this brief review, the Annex 6 of the *Global Forest Resource Assessment 2010* (FAO, 2010b) has been used as main source.

[13] It must be noted that total forest values from these mentioned sources are the same as FAO Production Yearbook not rarely.

[14] 10% canopy cover density, minimum tree height of 7 m and 10 he as the minimum area.

important to mention the differentiation in forest parameters between these two groups: 20% of crown cover threshold for industrialized and 10% for developing countries.

Going further, FRA 1990 is made up of different assessments covering several topics and regional areas: a global synthesis (FAO, 1995b), an assessment for tropical countries (FAO, 1993), two assessments for non-tropical developing countries (FAO, 1994; FAO, 1995c), one concerning forest plantations (FAO, 1995e), and a survey on tropical forest cover change (FAO, 1995d). This FRA has been characterized by its total coverage of developing and industrialized countries and by the implementation of a computerized deforestation model.[15] The use of this model has been implemented in order to overcome the bias in expert opinions in predicting forest cover changes, thus deforestation rates. Although the model increased data uniformity and enlarged the prediction for states characterized by a lack of data, deforestation rates are regressed against few right-hand variables (*e.g.* population density) decreasing the precision of estimates.[16] However, aware of these uncertainties deriving from the deforestation model, within this FRA has also been implemented a remote sensing survey (FAO, 1995d).[17] Lastly, even this assessment provided different quantitative data among developing and industrialized countries. Some updates and harmonizations of FRA 1990 data—but only for developing countries—have been made through the interim assessment *State of the World's Forests 1997* (FAO, 1997b).

With FRA 2000 (FAO, 2001b) for the first time a uniform definition of forest—10% canopy cover—has been used for all countries. Consequently, data from 1990 has been adjusted following this new definition. Total forest change (1990-2000) are presented both for developing and industrialized countries but not for natural forest

[15]Data for this FRA was contained in the FAO's database FORIS but they refer to different periods. Thus, the so-called "deforestation model" was needed in order to adjust to common years (1980 and 1990) these values. This model (or a forest area adjustment function) correlates forest cover change in time with other variables such as population density and growth, initial forest cover, and the ecological zone of interest. The model is expressed in a form of a differential equation as follow:

$$\frac{dY}{dP} = b_1 * Y^{b_2} - b_3 * Y \qquad (2.1)$$

Where Y is the percentage of non-forested area in a subnational unit computed as: Y = 100 * (Total area - Forest cover area)/(Total area); P is the population density expressed in person per square kilometers; b_1, b_2, and b_3 are the model's parameters (FAO, 1993).

[16]The fact that FRA 1990 data has been predicted through this model prevents the use of some variables—above all population—in an econometric model for deforestation such as EKC-based models due to a possible rise of endogeneity in the model.

[17]This survey is based on a statistical sampling of world's tropical forest equivalent to 10%.

change since plantations for the latter group is reported only for 2000. Nevertheless, with this assessment it must be noted the increase in support provided to countries' forest data reporting. FRA 2005 (FAO, 2006a) involved 229 countries providing a specific country report for each of them covering 95% of the world's forest area. Furthermore, the category of natural forest cover has been enriched with a further important variable: primary forest[18] (Grainger, 2008). Data is provided both for developing and industrialized countries for three periods: 1990, 2000, and 2005 with a total amount of 40 forest variables. The time-length has been extended with the next FRA 2010 (FAO, 2010b) with a slight improvement of the number of involved countries (from 199 to 233) and a more than duplicate number of reported variables (from 40 to 90). Finally, FRA 2015 (FAO, 2015) represents the last up to date document for global forest cover data.[19] This assessment covers 234 countries and territories, composed by 114 specific country reports[20] which cover about 99% of global forest area. FRA 2015 provides data for five year points (1990, 2000, 2005, 2010, and 2015) with predictions for 2020 and 2030 for a total amount of 117 forest variables. MacDicken (2015) summarizes the main achievement obtained through this last assessment carrying out a brief analysis of the main strengths and weakness of this data in order to use them wisely and properly.[21]

2.3 Methodology

The aim to reconstruct the forest cover trend across countries and time it is for sure a tough task. Reliable forestry panel data is mainly available only starting from the nineties (FRA) or even more recently (Hansen *et al.*, 2013). However, FT and

[18]Few years after the introduction of this category, the work of Potapov *et al.* (2008) through remote sensing identified areas of Intact Forest Landscape (IFL). Recently Potapov *et al.* (2017) provided IFL data from 2000 to 2013 pointing out how this category is different from the category of primary forest provided by FAO since "primary forests are part of IFLs, which also include nonforest intact ecosystems where climatic, soil, or hydrological conditions prevent tree growth, temporally treeless areas after the natural disturbance (for example, wildfires), and water bodies. IFLs may also include areas affected by low-intensity and historic human influence, such as hunting, scattered small-scale shifting cultivation, and preindustrial selective logging"[p.1].

[19]The current definition of forest area is the following: "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" (FAO, 2012)[p.3].

[20]In absence of a specific report, estimates are made—even for previous FRA—through desk studies conducted following the existing literature as long as expert opinions (MacDicken, 2015).

[21]A Special Issue of the *Journal Forest Ecology and Management* contains a more detailed analysis of FRA 2015 data articulated among thirteen peer-reviewed papers (MacDicken *et al.*, 2015).

EKCd hypotheses require a long time in order occur. The study of the EKCd could be conducted even with a simple cross-country analysis, regressing the panel data with a simple OLS estimation. In this case, without taking into account the time, forests with different GDP levels would lie on a different level of the EKC curve. Nevertheless, the possibility to study this phenomena through a broad data panel, with long N and T, it is far more suitable for this study.

The reconstruction follows the methodology applied by Meyfroidt *et al.* (2010) in their work. The authors reconstructed the total forest cover change for fifteen countries using mainly FRA data.[22] Even though a comparison of values across different FRA is not always possible, they evaluated the consistency of the values across time in accordance with the FT hypothesis. Substantially, if data follows the FT's path they could be considered consistent. For example, comparing FRA data for Bangladesh between 1968 (Persson, 1974) and 1990 (FAO, 2015) could be considered feasible. In fact, even though data accuracy and definitions are different across the two sources, the value for 1968 is far higher than the one for 1990. This could be seen in accordance with the FT theory. After selecting different data point in time, the authors linked them by means of a spline interpolation. This choice could be seen as an improvement compared to the common linear interpolation used by FAO to link forest data. Therefore, this article represents the ground-floor of the reconstruction presented here. However, the present work differs from the one of Meyfroidt *et al.* (2010) for three main aspects.

First, the number of individuals is far wider. The main EKCd literature (*e.g.* Cropper and Griffiths, 1994; Bhattarai and Hammig, 2001; Culas, 2012) selected countries with a total amount of forest area of 1 million of hectares in 1990, a year just before the end of their panel data (1994). For the present study a similar choice has been made but referring to 2000 as base year since it represents a more reliable year. Therefore, a total amount of 114 countries[23] have been selected, both developing and developed, divided in the following regional groups: Africa (36), Asia and Oceania (25), Europe and North America (31), and Latin America (21). Table 2.1 lists the selected countries with total forest cover values for 2000 retrieved from the last FRA (FAO, 2015).

[22] Alongside FRA data, Meyfroidt *et al.* (2010) relied also on some specific publication or official national surveys, such as for India.

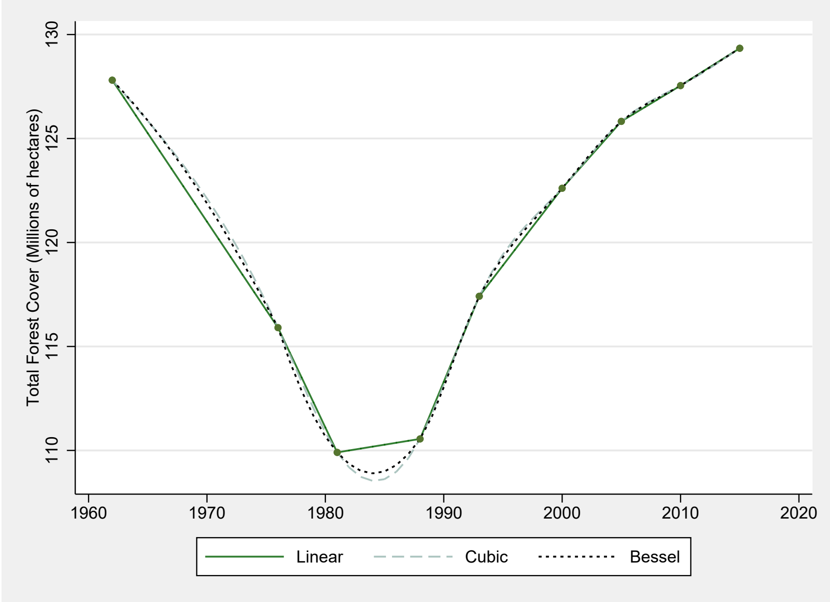
[23] The following countries have been excluded due to a lack of data: Afghanistan, French Guyana, People's Democratic Republic of North Korea, Turkmenistan, and Somalia. The lack of data refers to other variables used to test the EKCd—presented in the next chapter—first of all GDP per capita data. It must be said that North Korea, as one of the most closed economies and less democratic states, is experiencing highest rates of deforestation in the world (Hyde, 2012).

Table 2.1 *Total forest cover for selected countries (2000)*

Country	Region	Total Forest (ha)
Algeria	Africa	1,579,000
Angola	Africa	59,728,000
Benin	Africa	5,061,000
Botswana	Africa	12,535,325
Burkina Faso	Africa	6,248,000
Cameroon	Africa	22,116,000
Central African Republic	Africa	22,404,000
Chad	Africa	6,326,000
Congo (Democratic Republic of the)	Africa	157,249,000
Congo (Republic of the)	Africa	22,556,000
Cote d'Ivoire	Africa	10,328,000
Equatorial Guinea	Africa	1,743,000
Eritrea	Africa	1,576,000
Ethiopia	Africa	13,705,000
Gabon	Africa	22,000,000
Ghana	Africa	8,909,000
Guinea	Africa	6,904,000
Guinea-Bissau	Africa	2,120,000
Kenya	Africa	3,557,000
Liberia	Africa	4,629,000
Madagascar	Africa	13,023,000
Malawi	Africa	3,731,500
Mali	Africa	5,900,000
Morocco	Africa	4,993,000
Mozambique	Africa	41,188,000
Namibia	Africa	8,032,000
Niger	Africa	1,328,000
Nigeria	Africa	13,137,000
Senegal	Africa	8,898,000
Sierra Leone	Africa	2,922,000
South Africa	Africa	9,241,000
Sudan (former)	Africa	21,826,163
Tanzania (United Republic of)	Africa	51,920,000
Uganda	Africa	3,869,000
Zambia	Africa	51,300,488
Zimbabwe	Africa	18,894,000
Bangladesh	Asia	1,468,000
Bhutan	Asia	2,606,000
Cambodia	Asia	11,546,000
China	Asia	177,000,500
India	Asia	65,390,000
Indonesia	Asia	96,087,000
Iran (Islamic Republic of)	Asia	9,325,660
Japan	Asia	24,876,000
Kazakhstan	Asia	3,365,000
Korea (Republic of)	Asia	6,288,000
Lao (People's Democratic Republic)	Asia	16,525,990
Malaysia	Asia	21,591,000
Mongolia	Asia	11,717,000
Myanmar	Asia	34,172,000
Nepal	Asia	3,900,000
Pakistan	Asia	2,116,000
Philippines	Asia	7,027,000

Sri Lanka	Asia	2,192,000
Thailand	Asia	17,011,000
Turkey	Asia	10,183,000
Uzbekistan	Asia	3,212,000
Vietnam	Asia	11,727,000
Austria	Europe	3,838,000
Belarus	Europe	8,273,000
Bosnia and Herzegovina	Europe	2,185,000
Bulgaria	Europe	3,375,000
Croatia	Europe	1,885,000
Czech Republic	Europe	2,637,000
Estonia	Europe	2,243,000
Finland	Europe	15,740,680
France	Europe	15,289,000
Georgia	Europe	2,760,600
Germany	Europe	11,354,000
Greece	Europe	3,601,000
Hungary	Europe	1,917,000
Italy	Europe	8,369,000
Latvia	Europe	3,241,000
Lithuania	Europe	2,020,000
Norway	Europe	12,113,000
Poland	Europe	9,059,000
Portugal	Europe	3,343,000
Romania	Europe	6,366,000
Russian Federation	Europe	809,268,500
Serbia	Europe	2,476,000
Slovak Republic	Europe	1,921,000
Slovenia	Europe	1,233,000
Spain	Europe	16,976,940
Sweden	Europe	28,163,000
Switzerland	Europe	1,194,000
Ukraine	Europe	9,510,000
United Kingdom	Europe	2,954,000
Argentina	Latin America	31,860,000
Belize	Latin America	1,459,300
Bolivia (Plurinational State of)	Latin America	60,091,000
Brazil	Latin America	521,274,000
Chile	Latin America	15,834,000
Colombia	Latin America	61,798,440
Costa Rica	Latin America	2,376,000
Cuba	Latin America	2,435,000
Dominican Republic	Latin America	1,486,000
Ecuador	Latin America	13,728,920
Guatemala	Latin America	4,208,000
Guyana	Latin America	16,622,000
Honduras	Latin America	6,392,000
Mexico	Latin America	67,856,000
Nicaragua	Latin America	3,814,000
Panama	Latin America	4,867,000
Paraguay	Latin America	19,368,000
Peru	Latin America	76,147,000
Suriname	Latin America	15,391,000
Uruguay	Latin America	1,369,700
Venezuela (Bolivarian Republic of)	Latin America	49,151,000

Figure 2.1 *China total forest cover (1962–2015), data interpolation (fudge factors)*



Source: Author's personal elaboration.

Canada	North America	347,802,000
United States of America	North America	303,536,000
Australia	Oceania	128,841,000
New Zealand	Oceania	10,139,000
Papua New Guinea	Oceania	33,600,000
Solomon Islands	Oceania	2,268,000

Source: FAO (2015).

Second, the interpolation methodology is slightly different. While Meyfroidt *et al.* (2010) relied on a cubic spline, the reconstruction for the present work has been made through a Bessel-spline interpolation (also known as parabolic blending) (De Boor *et al.*, 1978).[24] In fact, the cubic interpolation could lead to some unrealistic results between highly different points in time, thus the Bessel interpolation slightly smooths the interpolated values. The following Figure 2.1 shows the three different interpolation conducted for China's total forest cover (reconstructed by means of fudge factors). The difference between the linear (used by FAO) and the other two interpolations is rather obvious while differences between the cubic and the Bessel are quite minimal.

Third, the use of fudge factors to link values among different FRAs (and sources). Meyfroidt *et al.* (2010) used deforestation rates from FRA 1980 for the period 1975-1990 to carry out some reconstructions. Conversely, the present reconstruction

[24]Since the use of a spline interpolation in this context could lead to some negative results, when this occurred values have been adjusted *ad hoc* or through a linear interpolation.

Table 2.2 *Dominican Republic natural forest cover (1975–1990)*

Year	FRA 1980			FRA 1990			FRA 2015	Natural Forest Cover Values	
	Values	F. Factor	Def. Rate	Values	F. Factors	Def. Rate	Values	with F. Factors	with Def. Rates
1975	645,500							1,478,030.56	1,453,500
1980	629,000	2.2687	-3,500	1,252,000				1,440,249.77	1,437,000
1990				1,077,000	1.0093	-35,000	1,087,000	1,087,000	1,087,000

Source: Author's personal elaboration.

uses both fudge factors—where possible—and deforestation rates to carry out the reconstruction creating two different forest cover trends. The recent work of Liu *et al.* (2017) use a similar expedient to meld forest data from different sources and more specifically to lead back national inventories' data previous to 1990 to FRA 2010 data (FAO, 2010b). For this study, fudge factors have been identified in relating the value of the considered forest variables for the same year retrieved from different FRAs, then these fudge factors have been multiplied to previous values. The idea beyond the use of fudge factors is the willingness to harmonize forest cover values to common source—in this case the latest FRA. The following example shows a practical reconstruction by means of fudge factors. According to FRA 2015 (FAO, 2015), natural forest area for Dominican Republic in 1990 is 1,087,000 he, while the corresponding value for FRA 1990 (FAO, 1995b) is 1,077,000 he. Dividing the value of FRA 2015 by the one of FRA 1990 the obtained value (1.0093) represents a fudge factor. This value has been multiplied by the level of natural forest area for 1980 provided by FRA 1990 (1,427,000 he) obtaining 1,440,249.77 ha. Furthermore, the value of 1980 from FRA 1990 has been divided by the corresponding year-value retrieved from the Latin America report of FRA 1980 (FAO, 1976a) in order to obtain a second fudge factor (2.2687). Then the value from 1975 provided by FRA 1980 (645,500 he) has been multiplied by the two identified fudge factors (2.2687 for 1980 and 1.0093 for 1990) obtaining the final value of 1,478,030.56 he for 1975. Conversely, by using deforestation rates instead of fudge factors the values would have been different.[25] In fact, applying the deforestation rate provided by FRA 1990 (3,500 he/y between 1981–1990) to the value of natural forest for 1990 of FRA 2015, the corresponding value for 1980 is 1,437,000 he. Furthermore, this new value has been multiplied by the deforestation rate provided by FRA 1980 (3,300 he/y between 1980–1976) to obtain a final natural forest area of 1,453,500 he for 1975. Table 2.2 summarizes the values obtained.

[25]The more the fudge factors diverge from 1, the more the results between the reconstructions obtained through fudge factors and deforestation rates diverge too.

2.3.1 Main documentation consulted

Here is shown the main documentation consulted to retrieve total, natural, and planted forest data. The oldest document which collects forest data across countries is the work of Zon (1910) called *The Forest Resources of the World*.[26] However, this document has been consulted only to have a glance of a long span of forest cover trends.[27] The three *World Forest Inventory* of FAO (1957, 1960, 1963) followed by the book *The forest area of the world and its potential productivity* of Paterson (1956) as a secondary and comparative source. With regard to the seventies, the main source has been the *World Forest Resources* of Persson (1974) since it contains values for natural forest area and plantations (man-made forests) for developing countries and total forest area and plantations for developed countries.[28] Regional assessments of 1970s has been consulted as secondary sources (FAO, 1976a,b,c,d,e). Furthermore, regional assessments of FRA 1980 (FAO, 1981a,b,c,d) provided detailed values for natural forest area of developing tropical countries for the years 1975, 1980, and 1985 (estimated) while plantations data goes back to 1940 with five-yearly frequency. The Interim report of 1988 provided values even for developed countries but only for total forest cover area. Alongside these sources, for 1980s also data provide by the book *Managing the world's forests: looking for balance between conservation and development* by Sharma (1992) has been consulted. Going further, FRA 1990 (FAO, 1995b) has been used as main source for both developing (natural forest area and plantations for 1980 and 1990) and developed countries (total forest and deforestation rates 1980–1990 for all wooded area). Concerning forest plantations, for tropical countries the most comprehensive source is the specific *Tropical forest plantation resources* (FAO, 1995e) which provides several values between 1980 and 1990. Conversely, concerning non tropical developing countries, values for natural forest and plantations have been retrieved from the related specific assessment for non-tropical developing countries (FAO, 1995c).[29] Another consulted source for plantations from 1980 and 1990 is a specific working paper of FAO on forest plantations (FAO, 2001a). Data after 1990 has been retrieved from FRA 2015 consulting each country report for further data

[26]It has been followed by another important namesake work of Zon and Sparhawk (1923). Furthermore, another two worth-mentioning works are the reports of Myers (1980, 1989), focused only on tropical forests, but not used for the purpose of this work.

[27]In fact, since data for GDP considered (WB, 2017) begins in 1960, values too distant from this year have not been used for the reconstruction because beyond the time span of interest.

[28]Persson (1974) classifies values with a scale of accuracy from 1 (low) to 5 (high accuracy).

[29]The non tropical countries considered for the analysis are the following: Algeria, Argentina, Chile, China, Democratic Republic of Korea, Iran, Mongolia, Morocco, Tunisia, and Uruguay.

(FAO, 2014). Furthermore, even data and singular country reports provided by previous FRA (FAO, 2005, 2010c) have been consulted where necessary in order to be aware of some main changes among editions.[30] Lastly, for some countries alongside official data, specific publications and researches have been consulted to enrich and validate the reconstruction.

2.3.2 The question of planted forests

The reconstruction of historical trends of this forest category deserves a separate mention because, even if "planted forest cover less than 3% of land area [7% of total forest area], they contribute a considerably higher proportion of overall goods (wood, fiber, fuel) and environmental and social services, now, and increasingly in the future" Evans (2009)[p.3]. Furthermore, according to FAO (2015) the total amount of planted forest is nearly 300 millions of hectares, representing more than 13% of world forests. However, the relevance of this category reflects its hurdle in classification. The reconstruction of the trend in planted forests represents a delicate topic since the definition of this category changed across time and among countries, especially between temperate and tropicals. The evolution of plantations changed with different purposes, from cultivations with mere production or commercial objectives to more recent protection, conservation, and recreational purposes (Evans, 2009).[31] Furthermore, the separating line between natural and planted forests has been always too blurred and the risk to fall into a category instead of another is extremely high.

Up until FRA 2005 the category of plantations considered only afforestation[32] and reforestation[33] activities. However, other two categories of forests tend to mingle with the one of plantations: forest established by natural regeneration with silvicultural intervention and manipulation and forests naturally regenerated without human actions. FRA 2005 reviewed the classification of forest—previous divided, for developing countries, only between natural forests and plantations since 1980—

[30]Data provided by FRA 2000 FAO (2001b) and *The State of the World's Forests 1997* FAO (1997b) has been consulted as well for completeness.

[31]Chapter 2 of Evans (2009) presents a short but exhaustive excursus of the history of tree planting.

[32]The act of create forest in lands historically not covered by forests.

[33]The act of restore an area previous characterized by forest. The reforestation process could restore the previously existing crops or not or it could turn the land into mono-cultures.

adding also the classes of modified natural forests[34] and semi-natural forests[35] (Evans, 2009). The result has been a nomenclature change, from *forest plantations* to *planted forest* and it represents for sure an important watershed in the definition of this forest typology. The new concept of planted forest developed with FRA 2005 joined two forest categories formerly considered separately: plantation forests and planted semi-natural forests. Furthermore, this FRA has been accompanied by a specific working paper (FAO, 2006b) focused on plantations which conducted an in-depth analysis on planted forests through the submissions of specific questionnaires to a selection of 61 countries.[36] Among the new continuum of forest categories of FRA 2005, this study followed the differentiation presented in Table 2.3 which aims to identify the link between the different forest subgroups of productive and unproductive forest plantation and semi-natural forests. Unfortunately, this specific study has been conducted only for FRA 2005.

The definition of forest plantations/planted forest has changed and evolved across different FRA.[37] The last two FRAs did not change the definition of planted forests—and the relative sub-categories—according to the *Terms and Definitions* documents of these two assessments (FAO, 2010a; FAO, 2012).[38] However, a long-term reconstruction of these trends it is obviously approximate not only for the differences of plantations across time and among countries, but also because data often refers to planted area—or planned plantations—reported by the governments but not to the area that effectively survives.[39] Moreover, consulting various FRA editions, it is common to have very different values among sources for the same year. Considering all the limitations related to planted forest, the reconstruction has been conducted mainly through the use of fudge factors for developing countries and Persson (1974)'s data for developed ones starting from FRA 2015 data.

[34]Forests/other wooded land of naturally regenerated native species where there are clearly visible indications of human activities.

[35]Forest/other wooded land of native species, established through planting, seeding or assisted natural regeneration.

[36]Countries have been selected according to plantations forest reported to FRA 2000 (93.3% of total FRA plantation forest are in 1990). Of the whole sample 36 countries responded to the questionnaires and the remaining 25 countries have been included in a specific desk study.

[37]For example, starting with FRA 2000 the category of rubber plantations started to be included in the category of forest plantations (Grainger, 2009).

[38]Chapter 3 of Evans (2009) faces the matter of plantations' definitions.

[39]In order to shape these limitations, FAO deducts 30 % from the reported area to account the high mortality (Grainger, 2009).

Table 2.3 *Planted forests sub-group in the continuum of FRA 2005 categories*

			Planted forests subgroup		
				Plantations	
Primary	*Modified natural*	*Semi-natural*	*Planted component*	*Productive*	*Protective*
Forest of native species, where there are no clearly visible indications of human activities and the ecological processes are not significantly disturbed.	Forest of naturally regenerated native species where there are clearly visible indications of human activities.	Assisted natural regeneration through silvicultural practices for intensive management: weeding, fertilizing, thinning, and selective logging.	Forest of native species, established through planting, seeding, coppice.	Forest of introduced species and in some cases native species, established through planting or seeding, mainly for production of wood or non-wood goods.	Forest of native or introduced species, established through planting or seeding, mainly for provision of services.

Source: FAO (2006b).

2.3.3 Further considerations

Some conclusive considerations are required before moving on with the list of the reconstruction made for each country. Fudge factors have been used only where possible and deforestation rates only where available, thus mainly to reconstruct values for 1975 and 1980. Where possible, official data has been consulted and used, even in this case through fudge factors and deforestation rates to harmonize them to FRA data. The use of both deforestation rates and fudge factors has been applied only for developing countries. In fact, to take into account the diversification in forest cover between developing and industrialized countries—defined with the interim report of 1988 and made unique only with FRA 2000—the use of fudge factors seems to be the best solution.[40] Furthermore, concerning the three oldest resources consulted provided by FAO (1957, 1960, 1963), although the definition of forest land changed between the three editions,[41] they do not make a differentiation between natural forest and plantations. Whereby, plantation values mainly retrieved from FRA 1980's reports have been subtracted in order to obtain hypothetical values of natural forest cover. However, only few developing countries have notable amount of forest plantations for the years covered by the first FAO's assessments. Moreover, since industrialized countries have always received less attention by FAO, more detailed data on forest data—and more comparable with developing countries—have been available only with FRA 2000. Thus, for the reconstruction of this cluster

[40]Furthermore, the interim report of 1988 provided data for developed countries (with the forest closure threshold of 20%) without deforestation rates.

[41]Definitions of Forest land provided by FAO (1960) and FAO (1963) are similar and more specified instead of the one provided by FAO (1957), they are substantially equivalent. However, FAO's inventory of 1963 gives particular attention to the problems related to unstocked forest land. The results obtained by this inventory show how some states have over-reported the amounts of forest land. This is due because states reported as forest even land planned to be reforested or afforested not in a proper short and foreseeable future, and land administrated by forest services but treeless. Meyfroidt *et al.* (2010) use only data from FAO (1960) for their reconstruction.

of countries the total forest cover has been used and the trend of natural forest has been obtained by subtracting the yearly values of planted forest.

FRA 2015 data (FAO, 2015) have been primarily retrieved from the specific country reports submitted (FAO, 2014) which provide values for 1990, 2000, 2005, 2010, and 2015. However, this data does not take into account the historical changes among states[42] and have been submitted for each state for all of the five years into consideration. FRA 2015 could be retrieved also in the statistical portal of FAO, FAOSTAT (FAO, 2017a). Here values are linearly interpolated among years and historical events are considered but values for 2015 are not provided, conversely to WB (2017) which provides the same data with the inclusion of 2015. The following reconstructions, since it follows an its own interpolation, focused primarily on data provided by the country reports, secondary on FAOSTAT and WB data.

Eventually, it must be stressed that the analysis performed in the next chapter will use only data reconstructed by means of fudge factors for three main reasons. First, since the analysis will both consider developed and developing countries, the use of rates would have been possible only for the latter group according to FAO's data inventories. Second, data for planted forest has been reconstructed only with fudge factors since this approach would smooth differences in definitions among sources; therefore, since the EKCd investigates total forest, it would not have been optimal to sum natural and planted forest reconstructed with different approaches. Third, the fudge factors approach, despite limitations, is able to harmonize better data among countries retrieved from different FRAs, especially considering the change in classification occurred with FRA 2000.

2.4 The reconstruction of forest cover trends

This section summarizes the choices made to carry out the reconstruction in exams. The variables of interest are: *total forest cover*, *natural forest cover*, and *planted forest cover*. Each sub-section refers to a specific group of countries: Africa, Asia and Oceania, Europe and North America, and Latin America.[43]

[42]For example, countries of the former Soviet Union (as well as for former states of Yugoslavia, and Czechoslovakia) should not have values for 1990 since the dissolution of URSS occurred only in 1991. Another example is the former state of Sudan whose data should stop to 2011, year of the secession of the Republic of Sud Sudan.

[43]To simplify the exposition the following expedients have been made: fudge factors are abbreviated with FF and deforestation rates with DR; if not otherwise specified data from FRA 2015 refers to 1990, 2000, 2005, 2010, and 2015 abbreviated as 1990-2015 and they have been obtained consulting the specific country report submitted by countries; since the three regional reports of FRA 1980 (FAO,

2.4.1 Africa

Algeria

For this country, first the trend of total forest cover is calculated, then then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data starts with 1951 (the same value is provided by (FAO, 1957, 1960, 1963), followed by 1971 (Persson, 1974). Values for 1984 and 1990-2015 came from the country report for FRA 2015 (FAO, 2014). Planted forest data is provided for 1950 (FAO, 1976d), 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995c) followed by values of 1990-2015 (FAO, 2014). Total forest reconstruction has been made using country report's data, thus there is no difference between FF and DR data.

Angola

Natural forest cover data is retrieved from the country report for FRA 2015 (FAO, 2014) with values for 1970 and 1990-2015. Planted forest data is provided for 1960, 1965, 1970 (FF 1975) (FAO, 1976e), 1975, and 1990-2015 (FAO, 2014). Natural forest reconstruction has been made using country report's data, thus there is no difference between FF and DR data.

Benin

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980, 1983 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Botswana

Natural forest cover data is provided for 1980 (FF 1990) (FAO, 1995b) and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Concerning planted forest, their scarce presence is reported only by FAO (1995b,e) for the years 1980, 1984, and 1990. Whereby plantations have been

1981a,c,d) provide five-year data for tropical plantations, only the considered range is specified (*e.g.* 1960-1975); years used to obtain fudge factors are expressed in brackets and they have been obtained by comparing them with the same year values of the subsequent mentioned source.

considered only for this period even though starting with FAO (2001b) there is no presence of them even for 1990.

Burkina Faso

Natural forest cover data is provided for 1958 (FAO, 1960), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014).[44] The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1977, 1980, 1986, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Forest value for 1958 has been considered as natural forest since plantations programs started in 1975 (FAO, 1981c), thus previous values are negligible.

Cameroon

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FAO, 1981c) (FF 1980), 1978, 1980, 1982 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Central African Republic

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1970 (Persson, 1974) and 1990-2015 (FAO, 2014).

Chad

Natural forest cover data is provided for 1980 (FF 1990) (FAO, 1995b) and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1970 (Persson, 1974) and 1990-2015 (FAO, 2014). Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1977, 1980, 1982, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

[44] Data from FAO (1960, 1981c) refer to Burkina Faso as Upper Volta.

Congo (Democratic Republic of the)

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b),[45] and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) and 1980 (FF 1990) by FAO (1981c) and FAO (1995e) respectively, while the country report for FRA 2015 (FAO, 2014) provides planted forest values not only for 1990-2015 but also for 1982 and 1989.

Congo (Republic of the)

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1978, 1980, 1982, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Cote d'Ivoire

Natural forest cover data for 1958[46] (FAO, 1960) was obtained by subtracting to it the amount of plantations for 1960 provided by FAO (1981c). Subsequent values are provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Equatorial Guinea

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Regarding forest plantations, since there are some discrepancies among various sources, no presence of them have been reported before 1990 and for the forthcoming years data is retrieved from the country report for FRA 2015 (FAO, 2014).

[45] Consulted documents until 1997 refer to this country as Zaire.
[46] As part of the French West Africa.

Eritrea

Eritrea has been officially declared an independent state from Ethiopia in 1993. Thus, data for the three variables of interest is retrieved from the country report for FRA 2015 (FAO, 2014) covering the period 1990-2015.

Ethiopia

Considering the independence of Eritrea from Ethiopia, even for this country's data for the three forest variables is retrieved only from the country report for FRA 2015 (FAO, 2014) for the period 1990-2015. However, detailed data for this country (with Eritrea) previous to 1990 could be retrieved in the main reference literature utilized.

Gabon

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Ghana

Natural forest cover data for 1957 (FAO, 1960) and 1963 (FAO, 1963) was obtained by subtracting from them the amount of plantations for 1960 and 1965 (FAO, 1976e) respectively. Following values are provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1978, 1980, 1982, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Guinea

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Regarding forest plantations, data is for 1971 (Persson, 1974) and 1990-2015 (FAO, 2014).

Guinea-Bissau

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data is retrieved from the country report for FRA 2015 (FAO, 2014) for the years 1976 and 1990-2015. Concerning planted forest data is for 1970[47] (Persson, 1974) and 1990-2015 (FAO, 2014). Total forest reconstruction has been made using country report's data, thus there is no difference between FF and DR data.

Kenya

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1970 (FF 1980) (FAO, 1981c), 1976, 1980, 1981, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Liberia

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c) 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Madagascar

Natural forest cover data for 1962 (FAO, 1963) was obtained by subtracting from it the amount of plantations for 1960 provided by FAO (1981c). Subsequent values are provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Malawi

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover

[47] With the name of Portuguese Guinea.

data is provided by the country report for FRA 2015 for the years 1974 and 1990-2015 (FAO, 2014). Planted forest data is provided for the same years. Since total forest reconstruction has been made using country report's data, there is no difference between FF and DR data.

Mali

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90.Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980, 1981, 1984 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Morocco

Natural forest cover data is provided for 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Mozambique

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1979, 1980, 1983, 1984 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Namibia

Forest cover data is provided for 1960[48] by FAO (1960) and FAO (1963) and since no plantations are reported in Persson (1974), the amount of forest could be all classified as natural forest. Following data is retrieved for 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Concerning planted forests, some few amounts of them have been reporter by FAO (2001a) in contrast to other sources (Persson, 1974; FAO, 1993; FAO, 1995b). However, the reported value for 1990 is zero, the same

[48]With the name of South West Africa.

provided by the country report for FRA 2015 (FAO, 2014) which reports the existence of plantations only starting by 2005.

Niger

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1980, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Nigeria

Natural forest cover data for 1958 (FAO, 1963) was obtained by subtracting to it the amount of plantations for 1960 provided by FAO (1981c). Subsequent values are retrieved from the country's report for FRA 2015 for the years 1977 and 1990-2015 (FAO, 2014). This reconstruction has been carried out without the use of FF or DR. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1977 (FAO, 2014), 1980, 1984, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Senegal

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1978, 1980, 1982, 1984, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Sierra Leone

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data has all been retrieved from the country report for FRA 2015 for the years 1976, 1986, and 1990-2015 (FAO, 2014). Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1979, 1980, 1982, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Since total forest reconstruction has been made using country report's data, there is no difference between FF and DR data.

South Africa

Natural forest cover data is provided for 1980 (FF 1990) (FAO, 1995c) and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1969 (FAO, 1976e), 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Sudan (former)

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data is obtained by comparing values for 1990 provided by the country report for FRA 2005 (FAO, 2005) and 2015 (FAO, 2014) since the former gives values even for 1972 (FF 1990) (FAO, 1995c).[49] Data for 1990-2015 has been retrieved from the last country report. The reconstruction has been carried out even through DR used for the period 1972-90. Planted forest data is provided for 1969 (Persson, 1974), 1971 (Persson, 1974) and 1990-2015 (FAO, 2014).

Tanzania (United Republic of)

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1970 (FF 1980) (FAO, 1981c), 1977, 1980, 1982, 1985, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Uganda

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-1970 (FF 1980) (FAO, 1981c), 1980, 1982, 1984, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

[49] Values for former Sudan are obtained by a sum of forest data for Sudan and South Sudan of FRA 2015 (FAO, 2015). However, this data is remarkably different from the one provided by the two previous editions of the assessment (FAO, 2006a; FAO, 2010b).

Zambia

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data is obtained from the country report for FRA 2015 (FAO, 2014) for the years 1974 and 1990-2015. Planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981c), 1978, 1980, 1982, 1984, 1986 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Total forest reconstruction has been made using country report's data, thus there is no difference between FF and DR data.

Zimbabwe

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981c), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1965[50] (Persson, 1974), 1980, 1981, 1984, 1987, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Figures[51] 2.2, 2.3, and 2.4 show the reconstruction of the trend in total and natural forest cover made for the selected African countries through the use of FF. Furthermore, figures 2.5, 2.6, and 2.7 stress the difference on the reconstructions of natural forest cover between the use of FF and DR.

2.4.2 Asia and Oceania

This group is mainly characterized by developing countries except for Australia, Japan, New Zealand, and South Korea. For these mentioned countries the reconstruction has been carried out only through the use of fudge factors. The Russian Federation is not included in this cluster. However, some former states of the Soviet Union ar listed below and for them the reconstructions started only after the dissolution of Union of Soviet Socialist Republics (USSR) in 1991.

Australia

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover

[50] With the name of Rhodesia.

[51] These figures, as well as those for other country groups, are showed at the end of the chapter.

data starts with 1970 (Persson, 1974), followed by 1980 (FF 1990) (FAO, 1995b) and 1990-2015 (FAO, 2014). Planted forest data ais provided for the years 1960, 1967, 1971, 1972, 1974 (FAO, 1976b), and 1990-2015 (FAO, 2014). Since Australia is not a developing country, the reconstruction has been conducted only through FFs.

Bangladesh

Natural forest cover data is provided for 1968 (Persson, 1974), 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981d), 1976, 1978, 1980, 1982, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Bhutan

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981d), 1980, 1983 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Cambodia

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1967 (Persson, 1974) and 1990-2015 (FAO, 2014).

China

Natural and planted forest cover data is retrieved by comparing the values provided by NFIs and those of the country report for FRA 2015 (FAO, 2014). China has eight forestry inventories since the first edition (Zeng *et al.*, 2015). Data prior to the first inventory has not been considered (Song and Zhang, 2009). Furthermore, since the measurement of forest cover and volume changed with the fifth edition of the inventory (Hyde *et al.*, 2008), only the first four of them have been considered and compared to FRA 2015 data (1993 FF) (FAO, 2017a). The same procedure was followed for plantation data too. The reconstruction covers the years 1976, 1981, 1988 (Song and Zhang, 2009), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1981-88 and 1988-93.

India

Since the national inventory does not distinguish between natural forests and plantations and because of some changes made between different editions (Grainger, 2009), for this country only FAO's sources have been used for the reconstruction. Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1972 (Persson, 1974) and 1990-2015 (FAO, 2014).

Indonesia

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data starts with 1950 with data provided by Hannibal (1950) and Barber *et al.* (2002) which have been revised in a recent work carried out by Tsujino *et al.* (2016) focused on the history of forest loss in Indonesia. Further data refers to 1970 (Persson, 1974), 1985 (Barber *et al.*, 2002; Tsujino *et al.*, 2016) and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1963 (FAO, 1966), 1967, 1972 (Persson, 1974) and 1990-2015 (FAO, 2014). Although the reconstruction could be possible even with the use of FF and DR for the period 1975-1990 (and 1960-1990 for the planted forest), this possibility has been discarded since FAO's data for this period considers East Timor[52] as part of Indonesia. Furthermore, since total forest reconstruction has been made using country report's data, there is no difference between FF and DR data.

Iran

Natural forest cover data is provided for 1980 (FF 1990) (FAO, 1995c) and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1970 (Persson, 1974), 1980 (FF 1990) (FAO, 1995c), and 1990-2015 (FAO, 2014).

[52]Independent since 2002.

Japan

Natural and planted forest cover data is retrieved by comparing the values provided by the *Historical Statistics of Japan* (Japan Statistics Bureau, 2012) and those of the country report for FRA 2015 (FAO, 2014). Data is provided for the following years: 1960, 1970, 1980 (FF 1990) (Japan Statistics Bureau, 2012), and 1990-2015 (FAO, 2014). Since Japan is not a developing country, the reconstruction has been conducted only through FFs.

Kazakhstan

Since Kazakhstan has been part of the former Soviet Union,[53] forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Korea (Republic of)

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover data for the years 1964 and 1980 (FF 1990) has been retrieved from Bae *et al.* (2012) while data for 1990-2015 from the country report for FRA 2015 (FAO, 2014). Planted forest data is provided for the years 1975 (FAO, 1976b) and 1990-2015 (FAO, 2014). Since South Korea is not a developing country, the reconstruction has been conducted only through FFs.

Lao (People's Democratic Republic)

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 2001a), and 1990-2015 (FAO, 2014).

Malaysia

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out

[53] In Paterson (1956) can be found a reference for the forest area in 1934 of the states once part of the Soviet Union.

even through DR used for the periods 1975-80 and 1980-90. Planted forest data for the reconstruction was divided between rubber plantations and other plantations. The former has been reconstructed with values for 1970 (Persson, 1974) and 1990-2015 (FAO, 2014), the latter for 1960-75 (FF 1980) (FAO, 1981d), 1980, 1983, 1985, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Thereafter, the two plantations reconstruction have been joined in one single plantations trend for the period 1970-2015.

Mongolia

Natural forest cover reconstruction data starts with 1947, the same value is reported in the three FAO's forestry inventories consulted (FAO, 1957; FAO, 1960; FAO, 1963). Since the country report for FRA 2015 shows no presence of plantations in 1972, the value for 1947 could be fairly considered as the amount of natural forest. Subsequent values are for the years 1972 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for the years 1972 and 1990-2015 by (FAO, 2014).

Myanmar

Natural forest cover reconstruction data starts in 1955 with the value on forest cover reported by (Persson, 1974) which has been considered utterly formed by natural forests since no plantations are reported before 1970 (FAO, 1981d).[54] Therefore, the reconstruction is provided for 1975 (FF 1990) and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used to obtain data for 1970. Planted forest data is provided for 1981, 1985, and 1990-2015 (FAO, 2014) assuming a zero amount of plantations in 1965 as reported by (FAO, 1981d).

Nepal

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981d), 1975, 1980, 1986 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

[54] With the name of Bruma.

New Zeland

Natural forest cover data is retrieved by comparing the values provided by the *New Zealand Official Yearbook 2012* (Stats NZ's, 2013) and those of the country report for FRA 2015 (FAO, 2014). Data are provided for the following years: 1960, 1970, 1980 (FF 1990) (Stats NZ's, 2013), and 1990-2015 (FAO, 2014). Planted forest data is retrieved for 1936 (Stats NZ's, 2013), 1969 (Persson, 1974), 1985 (FF 1990) (FAO, 1997a), and 1990-2015 (FAO, 2014). Since New Zealand is not a developing country, the reconstruction has been conducted only through FFs.

Pakistan

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981d), 1980, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Papua New Guinea

Natural forest cover data for 1963 (FAO, 1963) was obtained by subtracting from it the amount of plantations for 1965 provided by FAO (1981d). Values for 1975 (FF 1980) and 1980 (FF 1990)have been retrieved from FAO (1981d) and FAO (1995b) respectively while values for 1990-2015 from the country report for FRA 2015 (FAO, 2014). The latest country report oddly sets to zero the presence of plantations starting to 1990 while their presence is clearly present in the two previous editions (FAO, 2005; FAO, 2010c). However, the same country report for FRA 2015 reports data about plantations in New Zealand between 1990 and 2010.[55] Whereby, the total amount of forest has been curtailed by those plantations data in order to obtain a proper amount of natural forest cover.[56] Furthermore, planted forest data is provided for 1960-1975 (FF 1980) (FAO, 1981d), 1977 (FAO, 2014), 1980, 1985, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

[55] Substantially, all plantations of Papua New Guinea have been converted to productive forests in FRA 2015.

[56] A prediction has been made for plantations data for 2015 according to data showed by the country report (FAO, 2014).

Philippines

Natural forest cover data for 1958 (FAO, 1960) was obtained by subtracting to it the amount of plantations for 1960 provided by FAO (1981d). Further values are provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981d), 1976, 1980, 1983, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Solomon Islands

Natural forest cover data is provided for 1953 (FAO, 1960; FAO, 1957), 1963 (FAO, 1963), 1972 (Persson, 1974),[57] 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1972 (Persson, 1974), 1980, 1984, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Sri Lanka

Natural forest cover data for 1962 (FAO, 1960) was obtained by subtracting to it the amount of plantations for 1960 provided by FAO (1981d). Further values are provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981d), 1976, 1980, 1984, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Thailand

Natural forest cover data is provided for 1964 (FAO, 1976b), 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1967 1969, 1971 (FAO, 1976b), 1976, 1980, 1982, 1985, 1989 (FF 1990) (FAO, 1981d), and 1990-2015 (FAO, 2014).

Turkey

For this country, first the trend of total forest cover is calculated, then natural forest cover data is obtained by subtracting the trend of planted forest. Total forest cover

[57] Until 1978 known as British Solomon Islands.

data is retrieved by comparing official data provided by the country report for FRA 2015 (FAO, 2014) with those reported for the assessment. Data is for the years 1973 (FF 1990) and 1990-2015. The reconstruction has been carried out even through DR used for the periods 1973-90. Regarding the planted forest, according to the last country report their beginning dates back in 1947, thus the reconstruction started with a zero value for this year followed by data for 1990-2015 (FAO, 2014).

Uzbekistan

Since Uzbekistan has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Vietnam

Natural forest cover data for 1958 (FAO, 1960)[58] was obtained by subtracting to it the amount of plantations for 1960 provided by FAO (1981d). Further values are provided for 1975 (FF 1980) (FAO, 1981d), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981d), 1979, 1980, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Figures 2.8 and 2.9 show the reconstruction of the trend in total and natural forest cover made for the selected countries of Asia and Oceania through the use of FF. Furthermore, figures 2.10 and 2.11 stress the difference on the reconstructions of natural forest cover between the use of FF and DR for developing countries of this cluster only.[59]

2.4.3 Europe and North America

This group is mainly characterized by developed countries except for the states once part of the former Soviet Union or under the communist influence.[60] For

[58]The value for this year joints the forest amount of North and South Vietnam.

[59]Australia, Japan, New Zealand, and South Korea are excluded in these figures since they are developed countries while Kazakhstan and Uzbekistan because former states of USSR.

[60]Considering the government and geographical changes occurred for these states at the beginning of the nineteens, only for few of these countries a reconstruction previous to 1990 has been feasible.

these developed countries the reconstruction has been carried out only through FF—primarily for 1990—in order to overcome the change in forest cover occurred with FRA 2000.[61] Furthermore, since data for developed countries did not differentiated between natural and planted forests before 2000, the reconstruction focused on total and planted forests while natural forest has been obtained by subtracting the former trend to the latter.

Austria

Total forest cover data has been reconstructed through values retrieved from the Austrian Forest Report 2015 (Foglar-Deinhardstein *et al.*, 2015) harmonized to FRA 2015 data by the use of FF. The reconstruction covers the years 1951, 1966, 1976, 1983 (FF 1990) (Foglar-Deinhardstein *et al.*, 2015), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Regarding natural forest data the reconstruction covers the period 1973-2015. The results, showed in the following tables, seems to be unrealistic due to the fact that the amount of Austrian plantations at the beginning of the seventies is almost equivalent to the total amount of forest as reported by Persson (1974).

Belarus

Since Belarus has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Bosnia and Herzegovina

Since Bosnia and Herzegovina has been part of the former Yugoslavia, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

However, although those states are considered as developing, they always have been treated in the same way and in the same cluster of Western European countries by FAO (FAO, 1976c).

[61] FFs has been obtained by comparing the value of total forest cover in 1990 provided by the country reports for FRA 2015 (FAO, 2014) and the corresponding value given by FRA 1990 (FAO, 1995b). Thereafter, those FFs have been multiplied by values for 1980 provided by the same FRA 1990 (they have been calculated considering the year change in forest and other woodland between 1980 and 1990) or, in absence of it, by values for the same year provided by the Interim report (FAO, 1988).

Bulgaria

Total forest cover data is provided for 1963 (FAO, 1960), 1967 (FAO, 1963), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Since there is no data about plantations before 1990 provided by FAO, the value for 1980 has been estimated by considering the plantation rate of the period 1990-2000. Values for the period 1990-2015 came from the country report for FRA 2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1980-2015.

Canada

Total forest cover data is provided for 1963 (FAO, 1963), 1980 (FF 1990) (FAO, 1988, 1995b), and 1990-2015 (FAO, 2014). Planted forest data has been obtained, following the methodology adopted even in the country report for FRA 2015, considering yearly values of total planted area and area of direct seeding, from 1975 to 2015 provided by the Canada's NFI. Thus values for planted forest area are provided for 1975, 1980, and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1975-2015.

Croatia

Since Croatia has been part of the former Yugoslavia, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Czech Republic

For this country data has been provided only for the years 2005, 2010, and 2015 as could be found in FRA 2015 (FAO, 2015)[62] even though FAOSTAT (FAO, 2017a) provides forest data back to 1993. However, since data provided by FRA 2010 (FAO, 2010b) is the same of FRA 2015, data for 1990 and 2010 has been retrieved from the corresponding country report of FRA 2010 (FAO, 2010c). Data does not go any further since Czech Republic alongside Slovakia were part of the former Czechoslovakia, dissolved in 1993.

[62] The country report of Czech Republic was not available on the FAO's website.

Estonia

Since Estonia has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Finland

Total forest cover data is provided for 1953 (FAO, 1960), 1963 (FAO, 1963), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

France

Total forest cover data is provided for 1953 (FAO, 1957), 1958 (FAO, 1960), 1967 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1965 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1965-2015.

Georgia

Since Georgia has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Germany

Total forest cover data is provided for 1958 (FAO, 1960), 1963 (FAO, 1963),[63] 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Since there is no data about plantations for East Germany,[64] the value for 1980 has been estimated by considering the plantation rate of the period 1990-2000. Values for the period 1990-2015 came from the country report for FRA 2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1980-2015.

[63] The value for these years joints the forest amount of West and East Germany using as leading year the first one since had the largest share in forest cover.

[64] Only for West Germany for 1973 (Persson, 1974).

Greece

Total forest cover data is provided for 1958 (FAO, 1960), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

Hungary

Total forest cover data is provided for 1950 (FAO, 1957), 1958 (FAO, 1960), 1963 (FAO, 1963), 1966 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1965 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1965-2015.

Italy

Total forest cover data is provided for 1952 (FAO, 1960), 1963 (FAO, 1963), 1985, and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974), 1985, and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

Latvia

Since Latvia has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Lithuania

Since Lithuania has been part of the former Soviet Union, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Norway

Total forest cover data is provided for 1958 (FAO, 1960), 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

Poland

Total forest cover data is provided for 1947 (FAO, 1957), 1960 (FAO, 1963), 1971 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015. Likely to Austria the results, showed in the following tables, seems to be unrealistic due to the fact that the amount of Poland plantations at the beginning of the seventies is almost equivalent to the total amount of forest (Persson, 1974).

Portugal

Total forest cover data is provided for 1948 (FAO, 1957), 1958 (FAO, 1960), 1963 (FAO, 1963), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1965 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1965-2015.

Romania

Total forest cover data is provided for 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Since there is no data about plantations before 1990 provided by FAO, the value for 1980 has been set equal to 1990 since no modification of the extend of plantations occurred between the decade 1990-2000. Values for the period 1990-2015 came from the country report for FRA 2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1980-2015.

Russian Federation

Since Russia represented the leader state of the former Soviet Union, forest data is provided only starting from 1990 and they have been retrieved only from the country report for FRA 2015 covering the period 1990-2015 (FAO, 2014). Although some sources provide information and data foregoing to 1990 for different states[65] of the Soviet Union, a reconstruction—even through FFs—would be difficult and unreliable.

[65] For example FRA 1990 (FAO, 1995b) provides data not only for the Soviet Union but also for other former members of this state such as Belarus and Ukraine. Furthermore, Zon (1910) and Paterson (1956) provided forest data about various states and areas of USSR.

Serbia

Since Serbia has been part of the former Yugoslavia, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Slovak Republic

Since Slovak Republic has been part of the former Czechoslovakia, forest data is provided only for the period 1990-2015 and has been retrieved from the country report for FRA 2015 (FAO, 2014).

Slovenia

Since Serbia has been part of the former Yugoslavia, forest data is provided only for the period 1990-2015 and have been retrieved from the country report for FRA 2015 (FAO, 2014).

Spain

For the reconstruction of the total amount of forest data the *Estadísticas históricas de España* (Albert and Xavier Tafunell, 2005) has been consulted for the years 1960, 1965, 1970, and 1975 (FF 1980, 1990). FFs have been obtained by comparing values of 1980 provided by Albert and Xavier Tafunell (2005) and by FRA 1990 (FAO, 1995b) and values of 1990 provided by FRA 1990 and FRA 2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

Sweden

Total forest cover data has been retrieved both from the country report for FRA 2015 and from the Swedish NFI which collected data since 1926. Values between the two sources have been harmonize through FFs obtained comparing values of 1990. From the NFI (SLU, 2017) data is five-yearly from 1955 to 1985 (FF 1990) while for the period 1990-2015 data is from the country report (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

Switzerland

Total forest cover data is provided for for 1952 (FAO, 1957), 1956 (FAO, 1960), 1963 (FAO, 1963), 1985, and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1965 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1965-2015.

Ukraine

Even for Ukraine, as well as all previous former states of the Soviet Union, data is provided only for the period 1990-2015. However, the country report for FRA 2015 provides data even for 1988 (FAO, 2014).

United Kingdom

Total forest cover data is provided for for 1953 (FAO, 1960),[66] 1963 (FAO, 1963), 1971 (Persson, 1974),[67] 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). Planted forest data is provided for the years 1973 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1973-2015.

United States of America

For the reconstruction of the total amount of forest official data have been used that was provided by US Department of Agriculture (USDA, 2014) harmonized through FFs (1997) to FRA 2015 data (FAO, 2014; FAO, 2017a). Values are provided for the following years: 1940, 1953, 1963, 1977, 1987, 1997, and 2000-2015. Planted forest data is provided for the years 1965 (Persson, 1974) and 1990-2015 (FAO, 2014). Concerning natural forest data the reconstruction covers the period 1965-2015.

Figures 2.12, 2.13, and 2.14 show the reconstruction of the trend in total and natural forest cover made for the selected countries of Europe and North America through the use of FF.

[66]Composed by Great Britain, Northern Ireland, Channle Islands, and Isle of Man. Values are provided for different years but the one of Great Britain was chosen as reference point since forest values of other members of UK are negligible.

[67]Values for 1963 and 1971 refer to Great Britain and Northern Ireland. The reference year is the one of the former.

2.4.4 Latin America

Argentina

Natural forest cover data for 1958 (FAO, 1960) was obtained by subtracting to it the amount of plantations for 1963 provided by FAO (1966). Further values are provided for 1972 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1963 (FAO, 1966), 1972 (Persson, 1974), 1980 (FF 1990) (FAO, 1995c), and 1990-2015 (FAO, 2014).

Belize

Natural forest cover data is provided for 1964 (FAO, 1963),[68] 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1983, 1984, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Bolivia (Plurinational State of)

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Brazil

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1975), 1975, 1980, 1982, 1985, 1986, 1988 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

[68] Until 1981 known as British Honduras.

Chile

Natural forest cover data for 1963 (FAO, 1963) was obtained by subtracting from it the amount of plantations for 1966 provided by Persson (1974). Further values are provided for 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the period 1980-90. Planted forest data is provided for 1966, 1970, 1972 (Persson, 1974), 1980 (FF 1990) (FAO, 2001a), and 1990-2015 (FAO, 2014).

Colombia

Natural forest cover data is provided for 1970 (Persson, 1974), 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1972 (Persson, 1974) and 1990-2015 (FAO, 2014).

Costa Rica

Natural forest cover data is provided for 1958 (Persson, 1974), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1975) (FAO, 1981a), 1980, 1984, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Forest cover value for 1958 has been considered as natural forest since values for 1960 provided by FAO (1981a) are negligible.[69] The work of Kleinn *et al.* (2002) has been consulted in order to follow a path of the forest cover trend of Costa Rica even though data is remarkably various among different sources.

Cuba

Natural forest cover data reconstruction starts with 1954 (FAO, 1957, 1960 and 1964 (FAO, 1963). For the former year data was considered as natural forest since no plantations are reported for 1960 by FAO (1981a), regarding the latter the value for natural forest as obtained by subtracting plantations for 1965 (FAO, 1981a). Successive values are provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided

[69] Although the value is negligible, after the reconstruction of planted forest trend through FFs, values of plantations for 1960 and subsequent years have become slightly higher.

for 1960-75 (FF 1980), 1980, 1987, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Dominican Republic

Natural forest cover data is provided for 1948 (FAO, 1957), 1958 (FAO, 1960, 1963), 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1984 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Forest cover values for 1949 and 1958 have been considered as natural forest since no plantations are reported before 1965 (FAO, 1981a).

Ecuador

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1978, 1980, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Guatemala

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1983 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Guyana

Natural forest cover data is provided for 1958 (FAO, 1960),[70] 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1983 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Forest cover value for 1958 has been considered as natural forest since no plantations are reported before 1965 (FAO, 1981a).

[70] Until 1966 known as British Guiana.

Honduras

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Regarding planted forest, no plantations are present between 1990 and 2015 according to the country report for FRA 2015 (FAO, 2014). Furthermore, even for 1970 no plantations are reported by Persson (1974). However, some plantations are reported by FAO (1995e) for 1990. Thus, only this amount of plantation has been considered, leaving zero plantations for 1980, 2000 and subsequent years. The reconstruction for planted forest cover trend expands from 1970 to 2015.

Mexico

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Concerning plantations, there is an elevated inaccuracy of data and huge differences between sources. Aware of that, for the reconstruction has been chosen one of the two value provided by Persson (1974), the one for 1973 since it is more in line with values provided by the country report for FRA 2015 for the period 1990-2015 (FAO, 2014).

Guyana

Natural forest cover data is provided for 1960 (FAO, 1963), 1970 (Persson, 1974), 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014). Forest cover value for 1960 has been considered as natural forest since no plantations are reported before 1970 (FAO, 1981a).

Panama

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1981, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Paraguay

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1982, 1985 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Peru

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-70 (FF 1980) (FAO, 1981a), 1975, 1980, 1985 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Suriname

Natural forest cover data is provided for 1975 (FF 1980) (FAO, 1981a), 1980 (FF 1990) (FAO, 1995b), and 1990-2015 (FAO, 2014). The reconstruction has been carried out even through DR used for the periods 1975-80 and 1980-90. Planted forest data is provided for 1960-75 (FF 1980) (FAO, 1981a), 1980, 1985, 1989 (FF 1990) (FAO, 1995e), and 1990-2015 (FAO, 2014).

Uruguay

Natural forest cover data has been retrieved only from the country report for FRA 2015 for the years 1980 and 1990-2015 (FAO, 2014). Since data came only form the latest FAO's source, the reconstruction has been made without the use of FF and DR. Concerning planted forest, data came from the same source and for the same years of natural forest but with the addition of 1962 (FAO, 1966).

Venezuela (Bolivarian Republic of)

Even for Venezuela forest cover data has been retrieved only from the country report for FRA 2015 for the years 1977 and 1990-2015 (FAO, 2014, 2017a),[71] thus the reconstruction has been made without the use of FF and DR. Concerning planted

[71] Actually, only data for 2010 and 2015 have been effectively reported in the country report while other data have been retrieved from FAOSTAT.

forest, data came from the same source and for the same years.

Figures 2.15 and 2.16 show the reconstruction of the trend in total and natural forest cover made for the selected countries of Asia and Oceania through the use of FF. Furthermore, figures 2.17 and 2.18 stress the difference on the reconstructions of natural forest cover between the use of FF and DR for developing countries of this cluster only.

2.5 Concluding remarks

The reconstruction presented in this chapter is the ground-floor for the following one which aims to re-assess and test—mindful of the previous literature and criticisms—the EKCd. The present work undoubtedly suffers from several flaws and limitations. Data among different FAO's sources is not always effectively comparable due to changes in definitions and accuracy of accountability. Figs. 2.2 to 2.18 which compare reconstructions made with fudge factors and deforestation rates show for some countries a remarkable difference due to high changes in forest cover values among different sources. Eventually, the whole reconstruction is affected by a certain degree of author's subjectivity. Despite—and aware—of all possible limitations, a similar reconstruction has never been carried out in this literature, thus used in order to test the EKCd and its long time-span could be fundamental for this purpose. Obviously this work represents just an attempt to reconstruct long forest cover time series and further improvements and reviews could be conducted to enrich the presented work undoubtedly.

The following Table 2.4 lists the countries for which the reconstructions have been made and the corresponding time span for total, natural, and planted forest cover.[72]

[72] Although for several countries the reconstruction has been realized starting from years before the sixties, the time span of the tables started only from 1960 corresponding to the first available data of the GDP variable used to test the EKCd (WB, 2017).

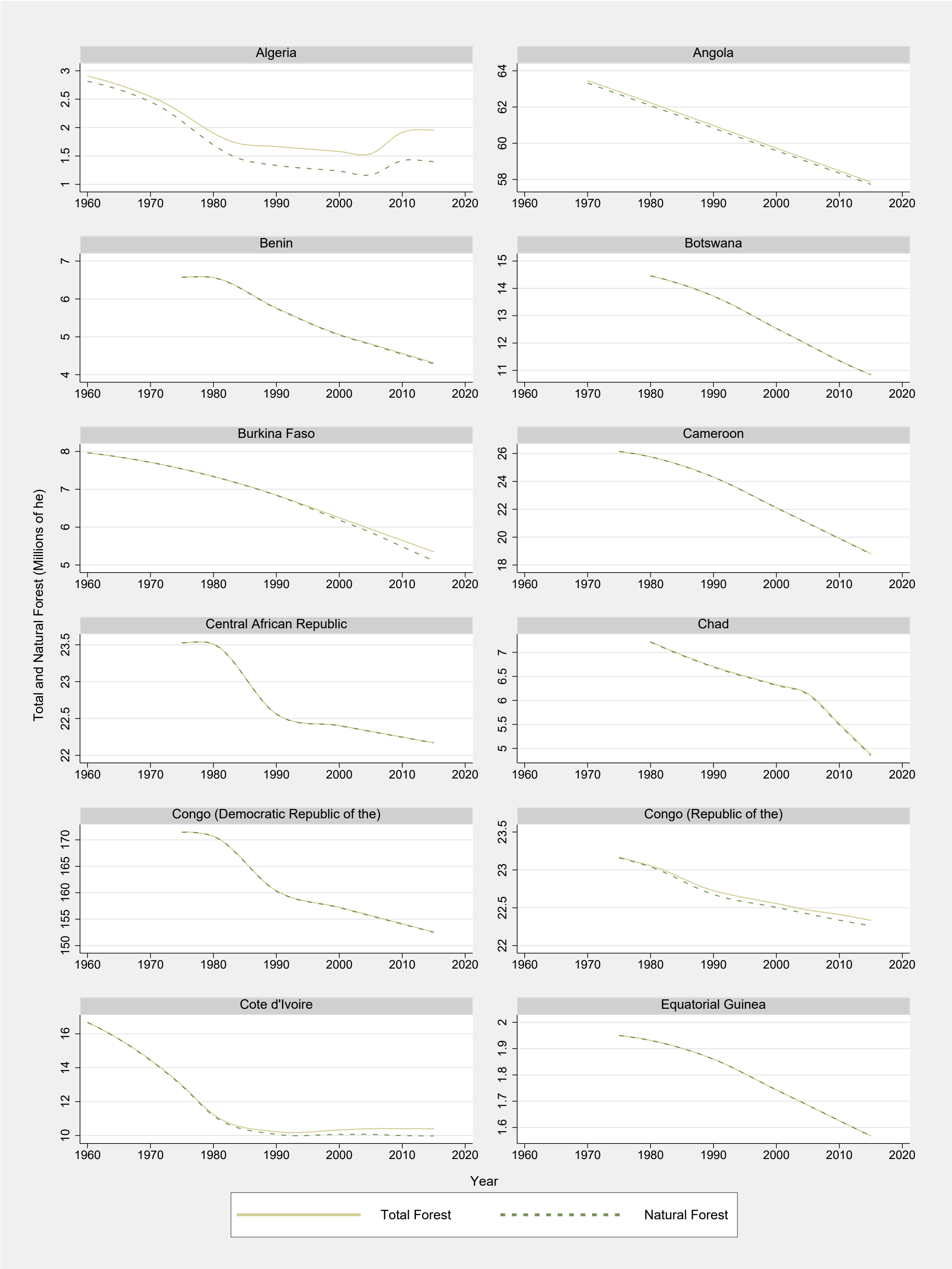
Table 2.4 *Forest cover trends for selected countries*

Country	Region	Forest Cover		
		Total	Natural	Planted
Algeria	Africa	1960-2015	1960-2015	1960-2015
Angola	Africa	1970-2015	1970-2015	1960-2015
Benin	Africa	1975-2015	1975-2015	1960-2015
Botswana	Africa	1980-2015	1980-2015	1960-2015
Burkina Faso	Africa	1960-2015	1960-2015	1960-2015
Cameroon	Africa	1975-2015	1975-2015	1960-2015
Central African Republic	Africa	1970-2015	1975-2015	1970-2015
Chad	Africa	1980-2015	1980-2015	1960-2015
Congo (Democratic Republic of the)	Africa	1975-2015	1975-2015	1960-2015
Congo (Republic of the)	Africa	1975-2015	1975-2015	1960-2015
Cote d'Ivoire	Africa	1960-2015	1960-2015	1960-2015
Equatorial Guinea	Africa	1975-2015	1975-2015	1960-2015
Eritrea	Africa	1990-2015	1990-2015	1990-2015
Ethiopia	Africa	1990-2015	1990-2015	1990-2015
Gabon	Africa	1975-2015	1975-2015	1960-2015
Ghana	Africa	1960-2015	1960-2015	1960-2015
Guinea	Africa	1975-2015	1975-2015	1971-2015
Guinea-Bissau	Africa	1976-2015	1976-2015	1970-2015
Kenya	Africa	1975-2015	1975-2015	1960-2015
Liberia	Africa	1975-2015	1975-2015	1960-2015
Madagascar	Africa	1962-2015	1962-2015	1960-2015
Malawi	Africa	1974-2015	1974-2015	1974-2015
Mali	Africa	1975-2015	1975-2015	1960-2015
Morocco	Africa	1971-2015	1971-2015	1971-2015
Mozambique	Africa	1975-2015	1975-2015	1960-2015
Namibia	Africa	1960-2015	1960-2015	1960-2015
Niger	Africa	1975-2015	1975-2015	1960-2015
Nigeria	Africa	1960-2015	1960-2015	1960-2015
Senegal	Africa	1975-2015	1975-2015	1960-2015
Sierra Leone	Africa	1976-2015	1976-2015	1960-2015
South Africa	Africa	1980-2015	1980-2015	1969-2015
Sudan (former)	Africa	1962-2015	1962-2015	1969-2015
Tanzania (United Republic of)	Africa	1975-2015	1975-2015	1960-2015
Uganda	Africa	1975-2015	1975-2015	1960-2015
Zambia	Africa	1974-2015	1974-2015	1960-2015
Zimbabwe	Africa	1975-2015	1975-2015	1965-2015
Bangladesh	Asia	1968-2015	1968-2015	1960-2015
Bhutan	Asia	1975-2015	1975-2015	1960-2015
Cambodia	Asia	1975-2015	1975-2015	1967-2015
China	Asia	1976-2015	1976-2015	1976-2015

India	Asia	1975-2015	1975-2015	1972-2015
Indonesia	Asia	1960-2015	1963-2015	1963-2015
Iran (Islamic Republic of)	Asia	1980-2015	1980-2015	1970-2015
Japan	Asia	1960-2015	1960-2015	1960-2015
Kazakhstan	Asia	1990-2015	1990-2015	1990-2015
Korea (Republic of)	Asia	1964-2015	1975-2015	1975-2015
Lao (People's Democratic Republic)	Asia	1975-2015	1975-2015	1960-2015
Malaysia	Asia	1975-2015	1975-2015	1970-2015
Mongolia	Asia	1960-2015	1960-2015	1960-2015
Myanmar	Asia	1960-2015	1960-2015	1960-2015
Nepal	Asia	1975-2015	1975-2015	1960-2015
Turkey	Asia	1973-2015	1973-2015	1960-2015
Pakistan	Asia	1975-2015	1975-2015	1960-2015
Philippines	Asia	1960-2015	1960-2015	1960-2015
Sri Lanka	Asia	1962-2015	1962-2015	1960-2015
Thailand	Asia	1964-2015	1964-2015	1960-2015
Uzbekistan	Asia	1990-2015	1990-2015	1990-2015
Vietnam	Asia	1960-2015	1960-2015	1960-2015
Austria	Europe	1960-2015	1980-2015	1980-2015
Belarus	Europe	1990-2015	1990-2015	1990-2015
Bosnia and Herzegovina	Europe	1990-2015	1990-2015	1990-2015
Bulgaria	Europe	1963-2015	1980-2015	1980-2015
Croatia	Europe	1990-2015	1990-2015	1990-2015
Czech Republic	Europe	1993-2015	1993-2015	1993-2015
Estonia	Europe	1990-2015	1990-2015	1990-2015
Finland	Europe	1960-2015	1973-2015	1973-2015
France	Europe	1960-2015	1965-2015	1965-2015
Georgia	Europe	1990-2015	1990-2015	1990-2015
Germany	Europe	1960-2015	1980-2015	1980-2015
Greece	Europe	1960-2015	1973-2015	1973-2015
Hungary	Europe	1960-2015	1965-2015	1965-2015
Italy	Europe	1960-2015	1973-2015	1973-2015
Latvia	Europe	1990-2015	1990-2015	1990-2015
Lithuania	Europe	1990-2015	1990-2015	1990-2015
Norway	Europe	1960-2015	1973-2015	1973-2015
Poland	Europe	1960-2015	1973-2015	1973-2015
Portugal	Europe	1960-2015	1965-2015	1965-2015
Romania	Europe	1980-2015	1980-2015	1980-2015
Russian Federation	Europe	1990-2015	1990-2015	1990-2015
Serbia	Europe	1990-2015	1990-2015	1990-2015
Slovak Republic	Europe	1990-2015	1990-2015	1990-2015
Slovenia	Europe	1990-2015	1990-2015	1990-2015
Spain	Europe	1960-2015	1973-2015	1973-2015
Sweden	Europe	1960-2015	1973-2015	1973-2015

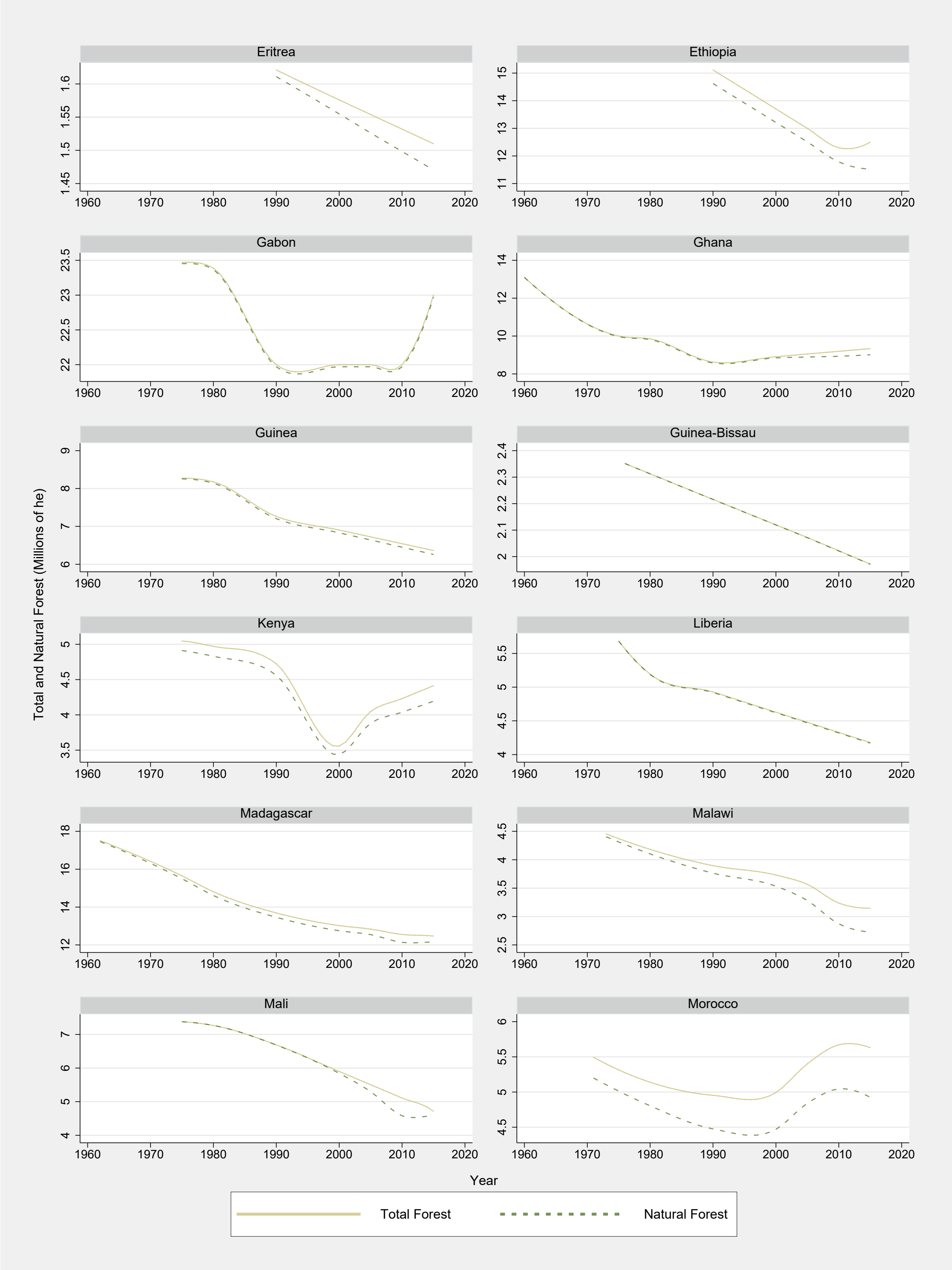
Switzerland	Europe	1960-2015	1965-2015	1965-2015
Ukraine	Europe	1988-2015	1988-2015	1988-2015
United Kingdom	Europe	1960-2015	1973-2015	1973-2015
Argentina	Latin America	1960-2015	1960-2015	1963-2015
Belize	Latin America	1965-2015	1965-2015	1960-2015
Bolivia (Plurinational State of)	Latin America	1975-2015	1975-2015	1960-2015
Brazil	Latin America	1975-2015	1975-2015	1960-2015
Chile	Latin America	1966-2015	1963-2015	1966-2015
Colombia	Latin America	1972-2105	1970-2015	1972-2105
Costa Rica	Latin America	1960-2015	1960-2015	1960-2015
Cuba	Latin America	1960-2015	1960-2015	1960-2015
Dominican Republic	Latin America	1960-2015	1960-2015	1960-2015
Ecuador	Latin America	1975-2015	1975-2015	1960-2015
Guatemala	Latin America	1975-2015	1975-2015	1960-2015
Guyana	Latin America	1960-2015	1960-2015	1960-2015
Honduras	Latin America	1975-2015	1975-2015	1970-2015
Mexico	Latin America	1975-2015	1975-2015	1973-2015
Nicaragua	Latin America	1960-2015	1960-2015	1960-2015
Panama	Latin America	1975-2015	1975-2015	1960-2015
Paraguay	Latin America	1975-2015	1975-2015	1960-2015
Peru	Latin America	1975-2015	1975-2015	1960-2015
Suriname	Latin America	1975-2015	1975-2015	1960-2015
Uruguay	Latin America	1980-2015	1980-2015	1962-2015
Venezuela (Bolivarian Republic of)	Latin America	1977-2015	1977-2015	1977-2015
Canada	North America	1963-2015	1973-2015	1973-2015
United States of America	North America	1960-2015	1960-2015	1960-2015
Australia	Oceania	1970-2015	1970-2015	1960-2015
New Zealand	Oceania	1960-2015	1960-2015	1960-2015
Papua New Guinea	Oceania	1963-2015	1963-2015	1960-2015
Solomon Islands	Oceania	1960-2015	1960-2015	1960-2015

Figure 2.2 *Africa: total and natural forest cover (1 of 3)*



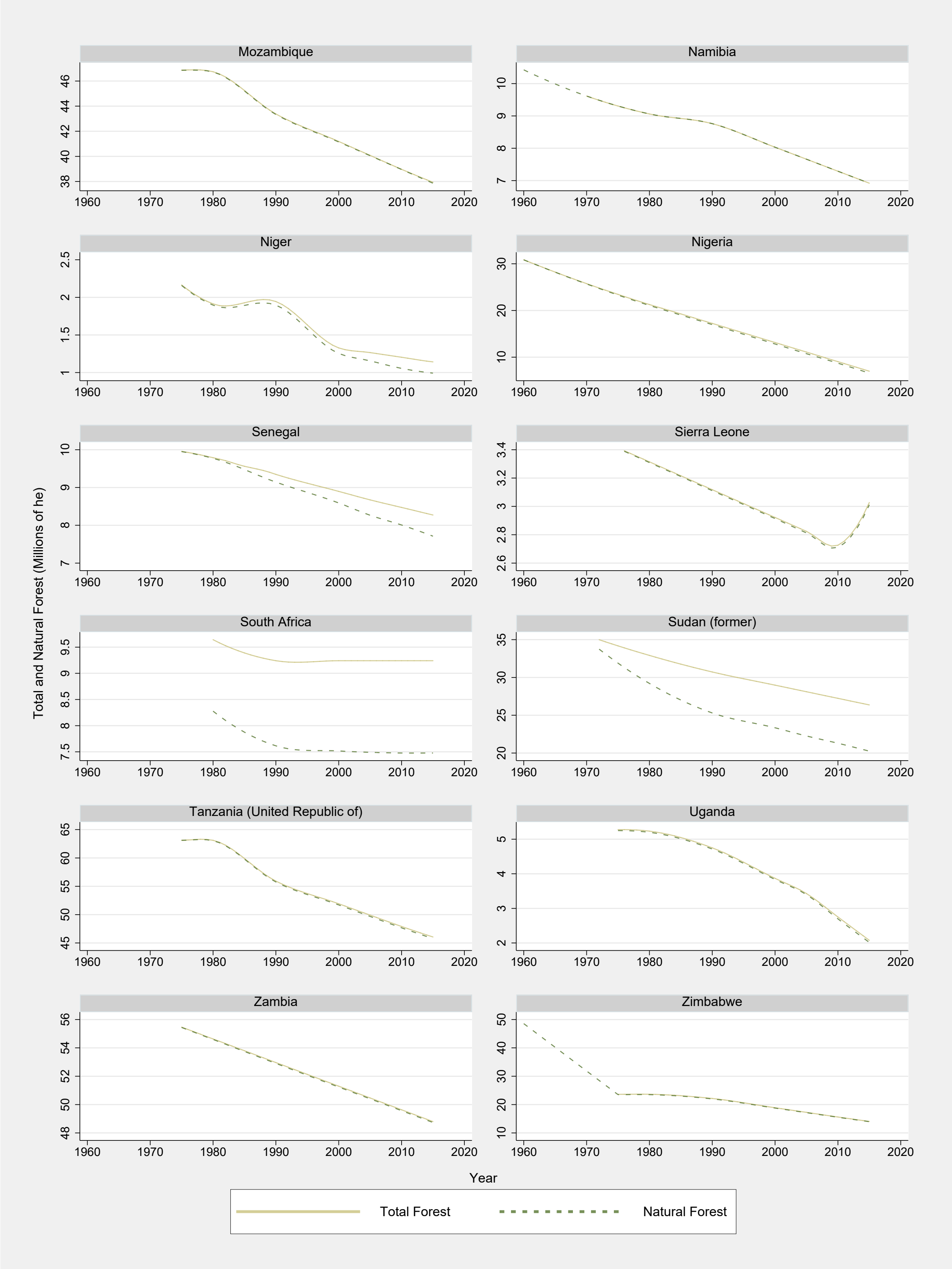
Note: Reconstruction carried out by means of fudge factors.

Figure 2.3 *Africa: total and natural forest cover (2 of 3)*



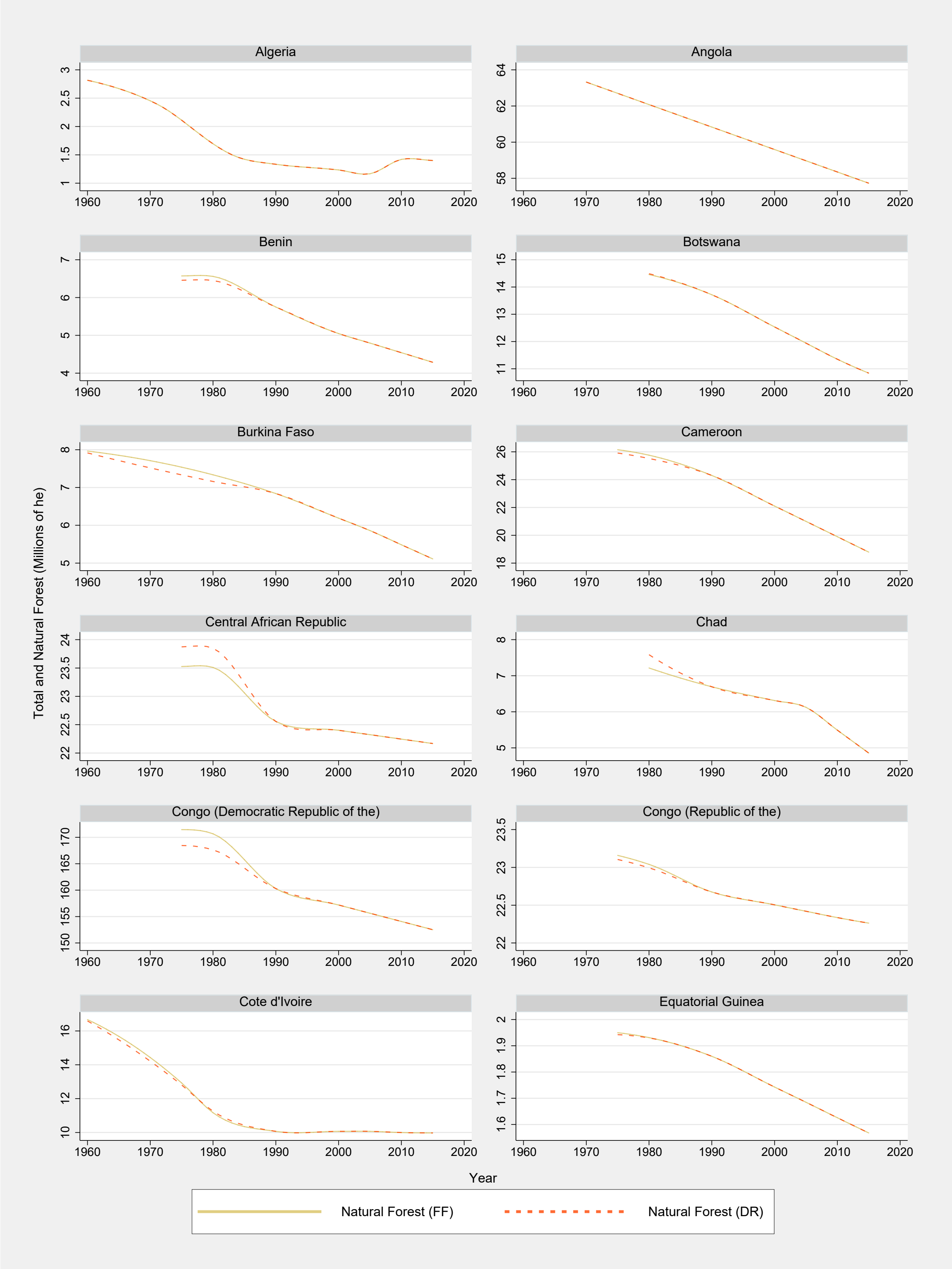
Note: Reconstruction carried out by means of fudge factors.

Figure 2.4 *Africa: total and natural forest cover (3 of 3)*



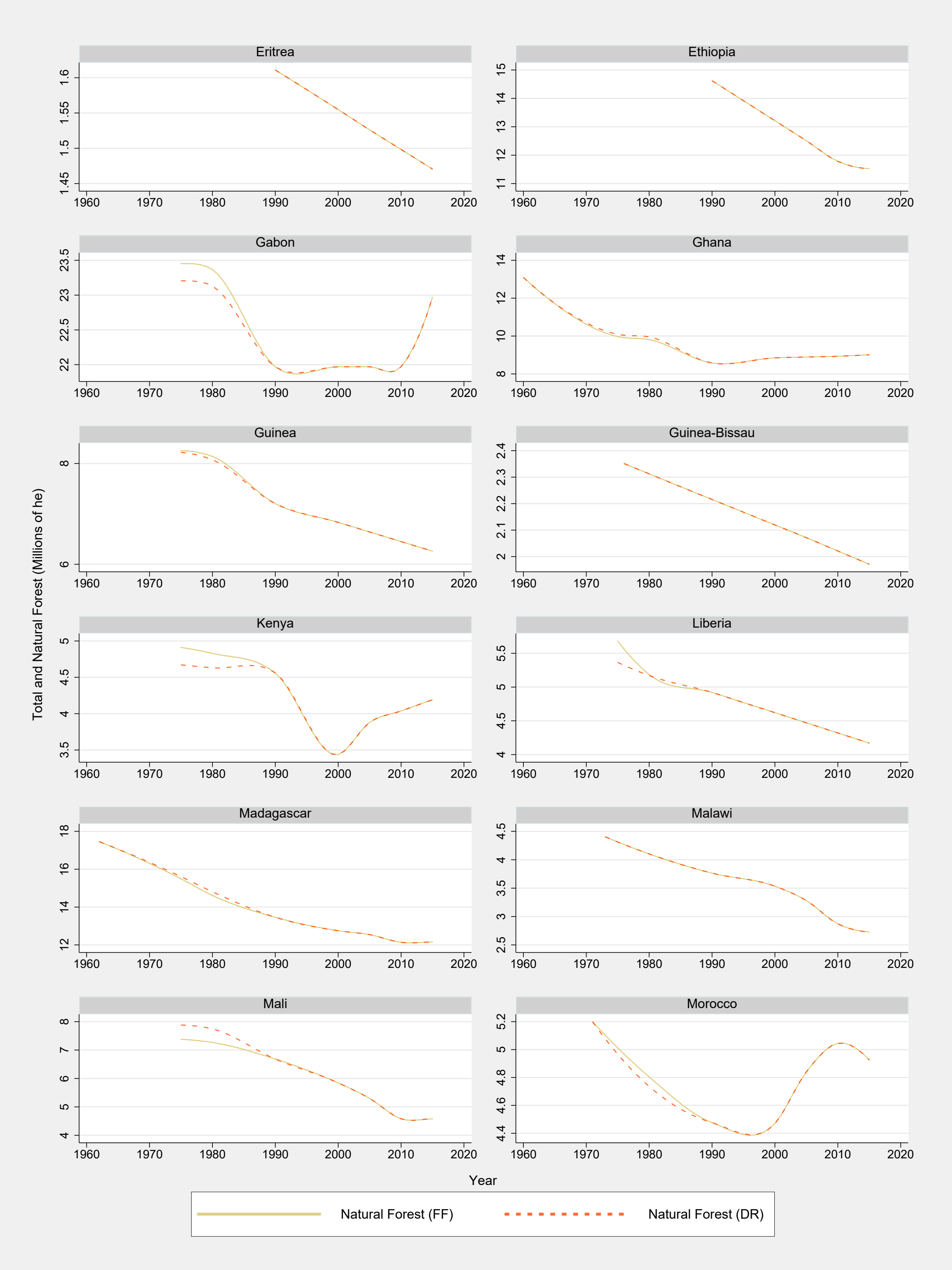
Note: Reconstruction carried out by means of fudge factors.

Figure 2.5 *Africa: natural forest cover with FF and DR (1 of 3)*



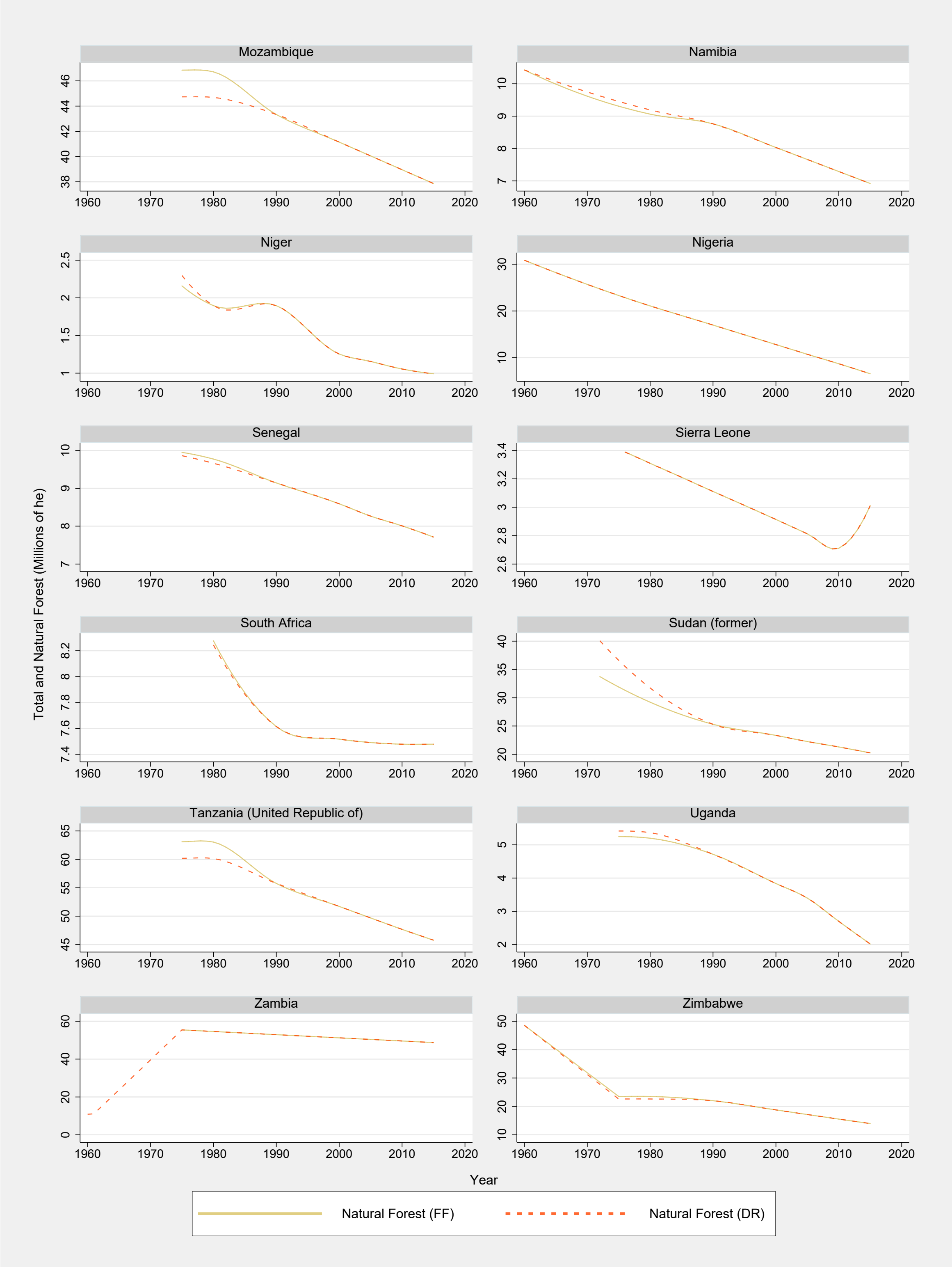
Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.6 *Africa: natural forest cover with FF and DR (2 of 3)*



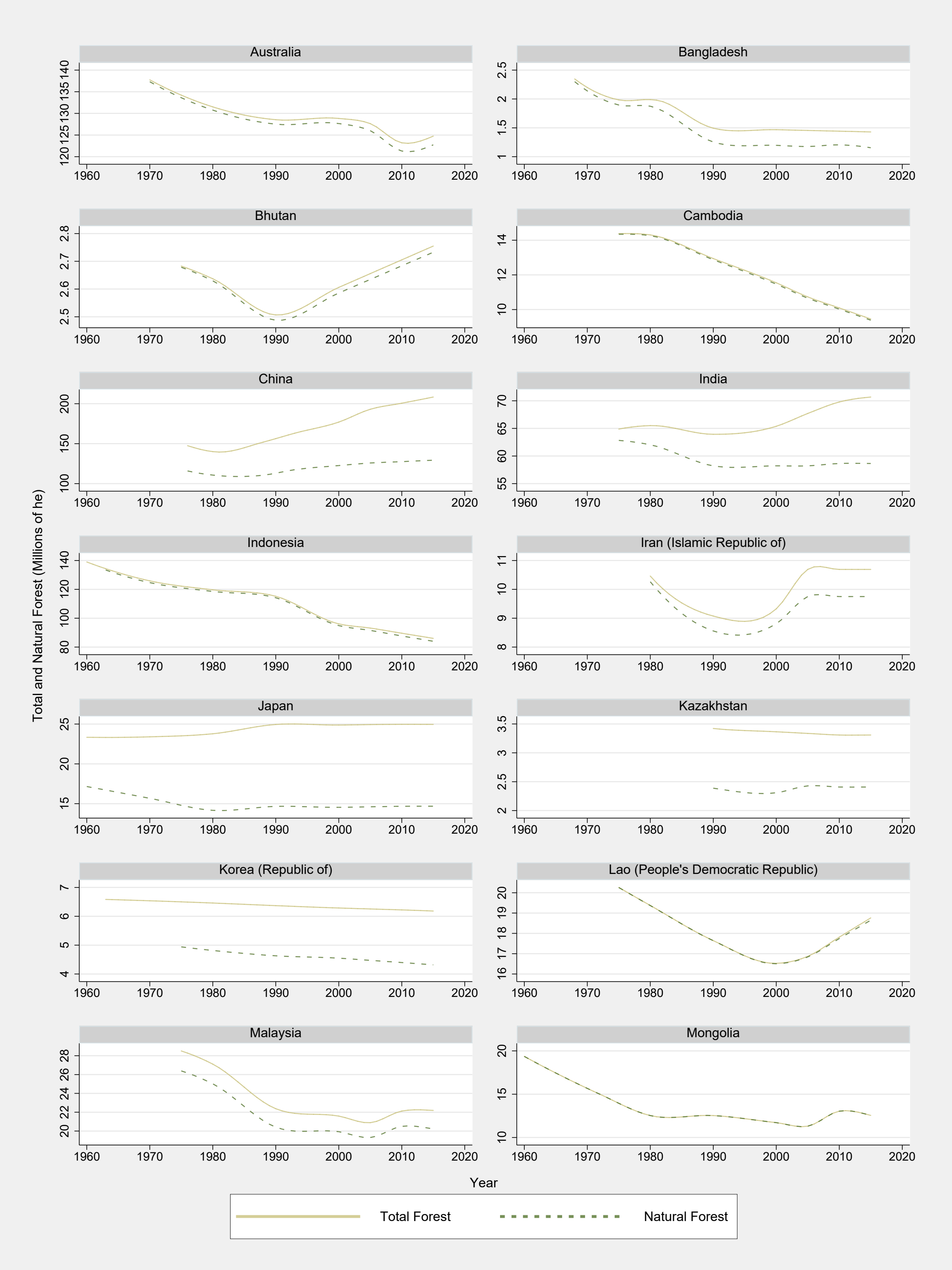
Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.7 *Africa: natural forest cover with FF and DR (3 of 3)*



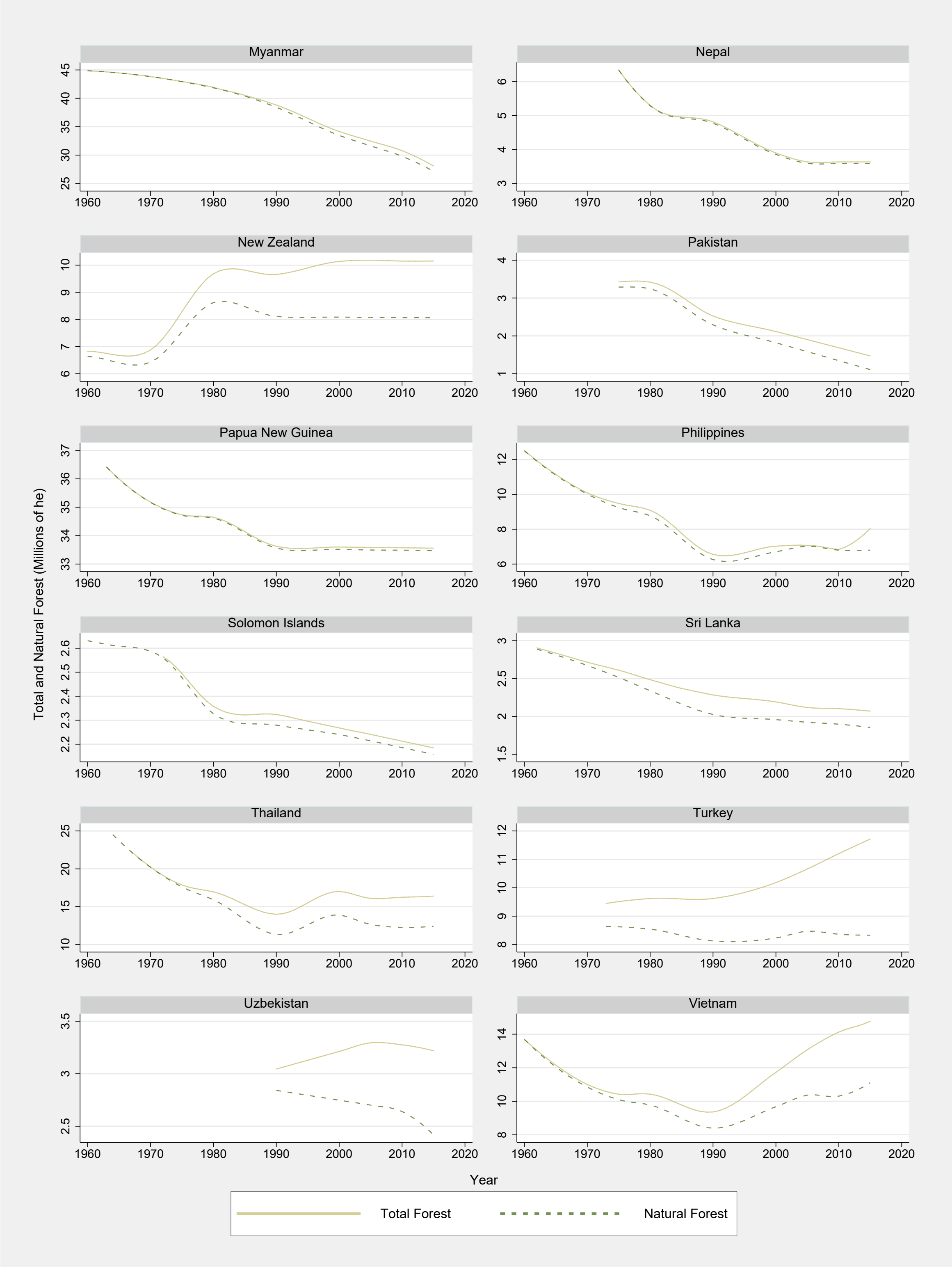
Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.8 *Asia and Oceania: total and natural forest cover (1 of 2)*



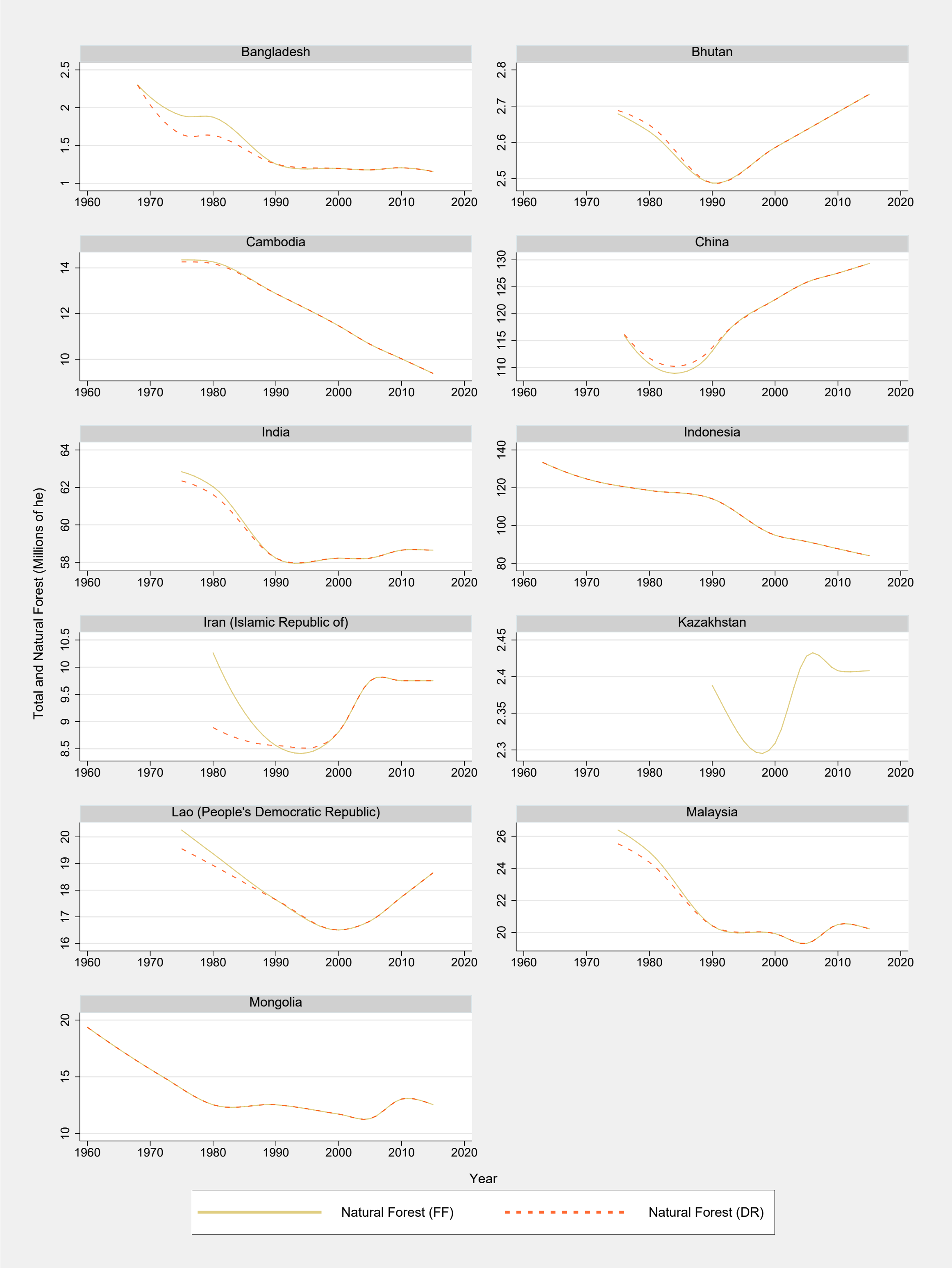
Note: Reconstruction carried out by means of fudge factors.

Figure 2.9 *Asia and Oceania: total and natural forest cover (2 of 2)*



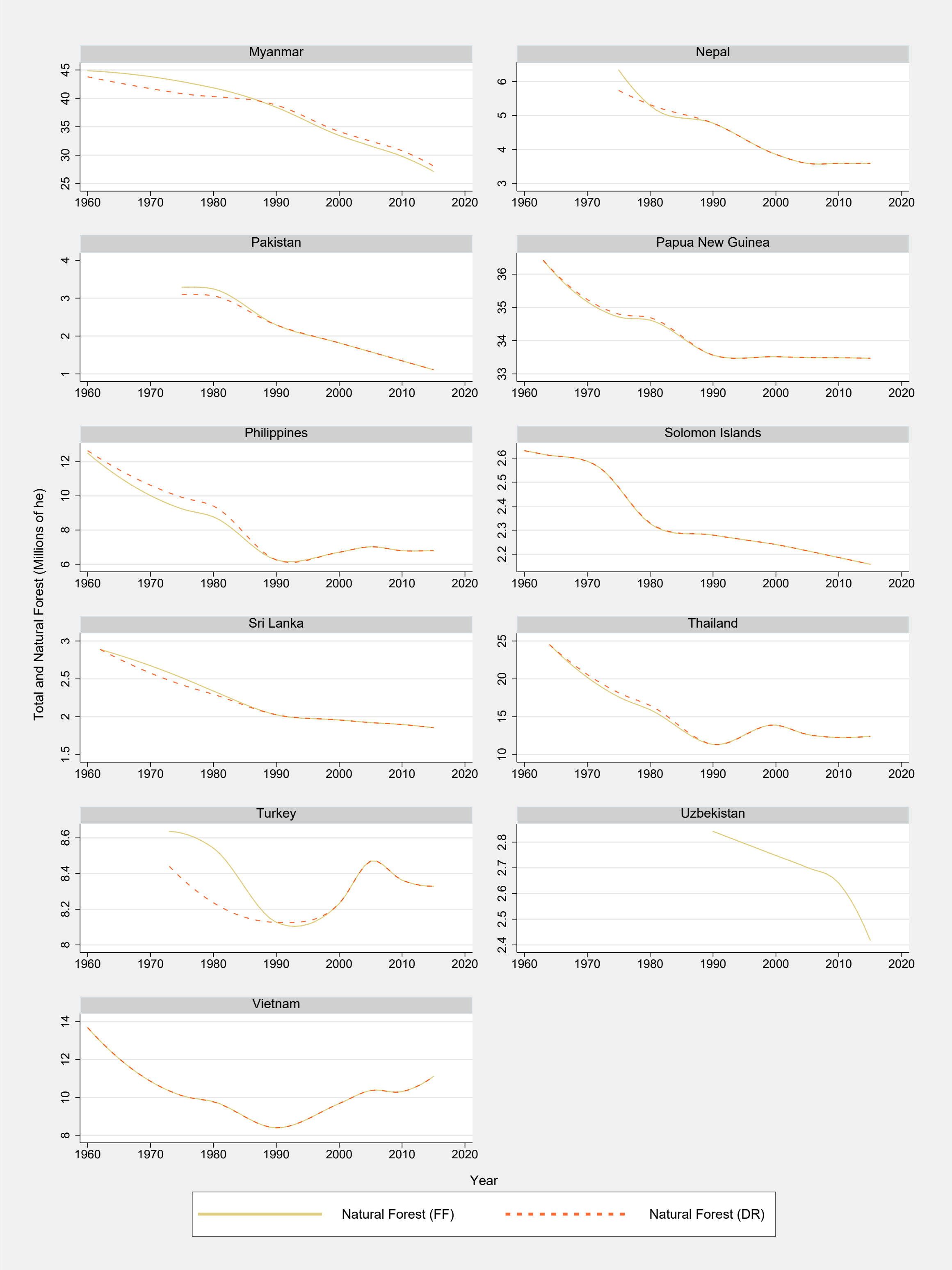
Note: Reconstruction carried out by means of fudge factors.

Figure 2.10 *Asia and Oceania: natural forest cover with FF and DR (1 of 2)*



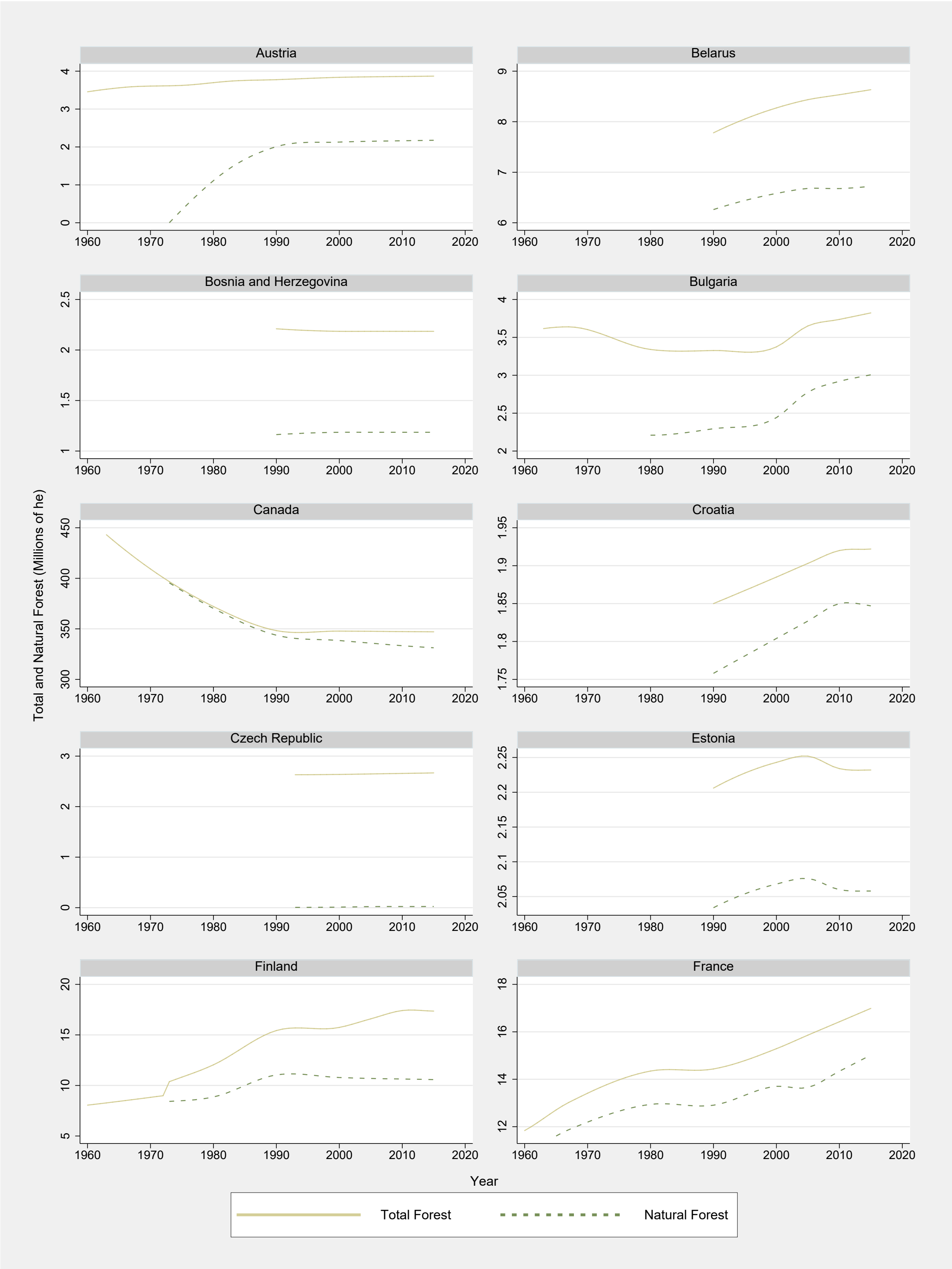
Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.11 *Asia and Oceania: natural forest cover with FF and DR (2 of 2)*



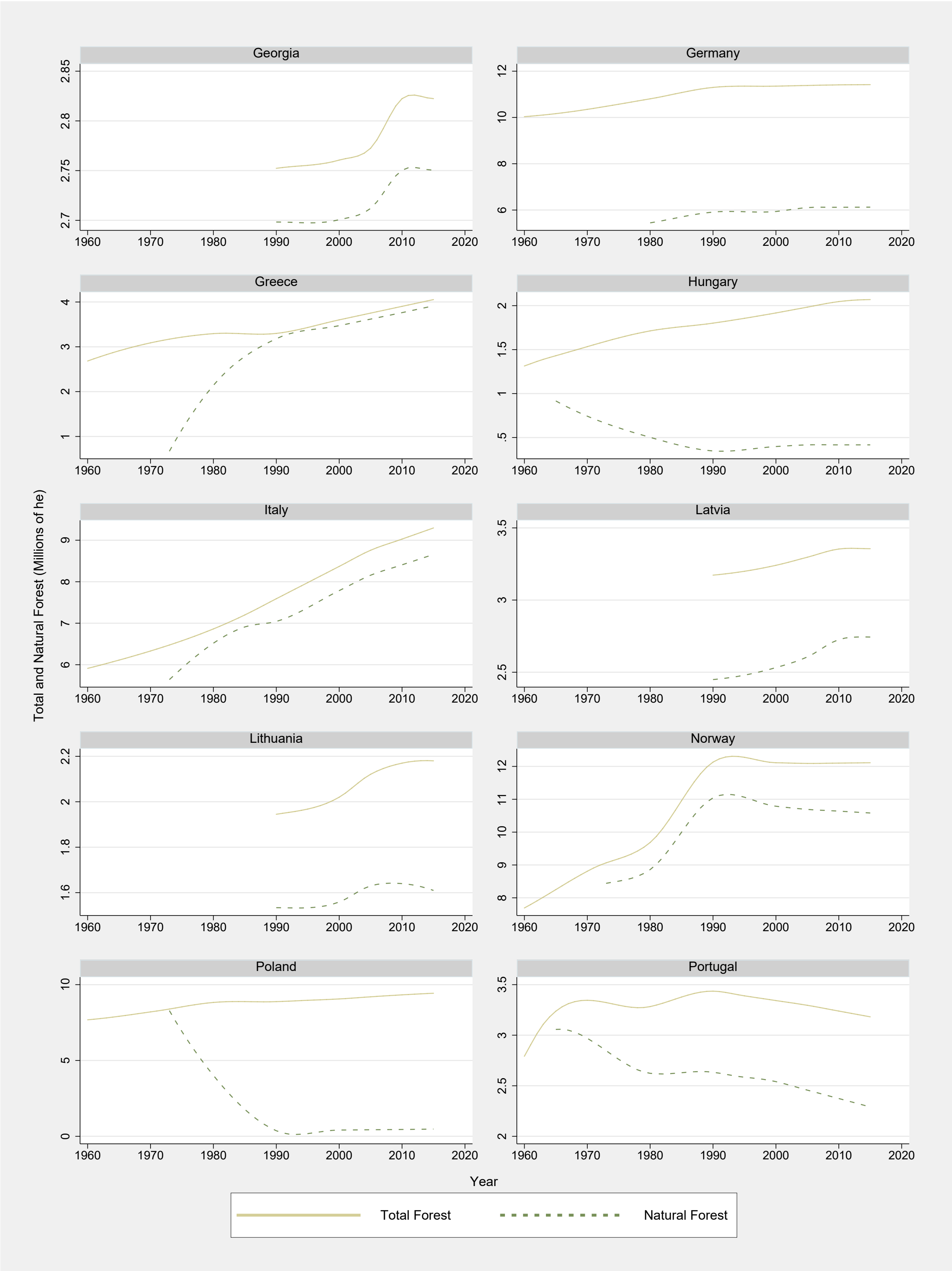
Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.12 *Europe and North America: total and natural forest cover (1 of 3)*



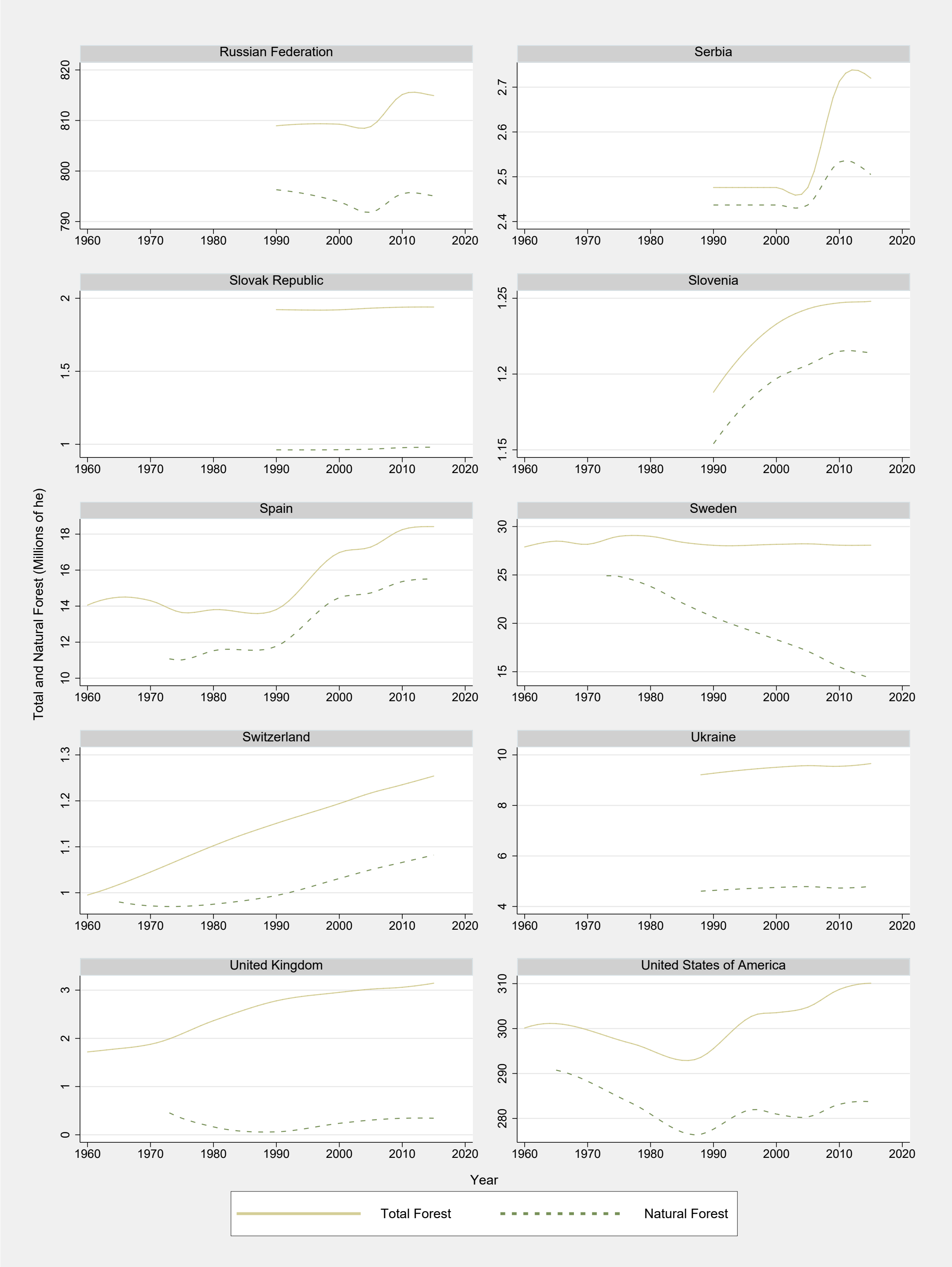
Note: Reconstruction carried out by means of fudge factors.

Figure 2.13 *Europe and North America: total and natural forest cover (2 of 3)*



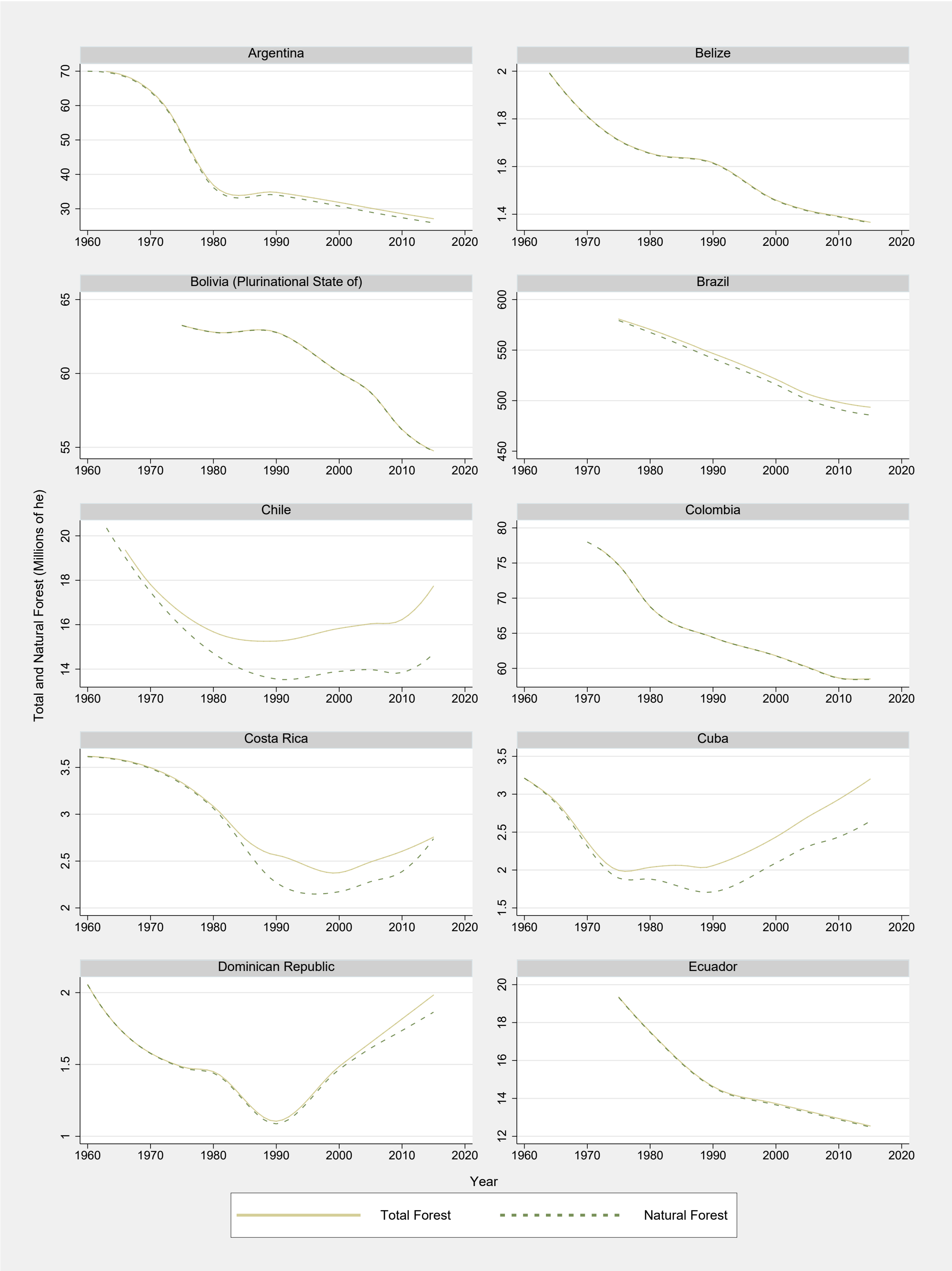
Note: Reconstruction carried out by means of fudge factors.

Figure 2.14 *Europe and North America: total and natural forest cover (3 of 3)*



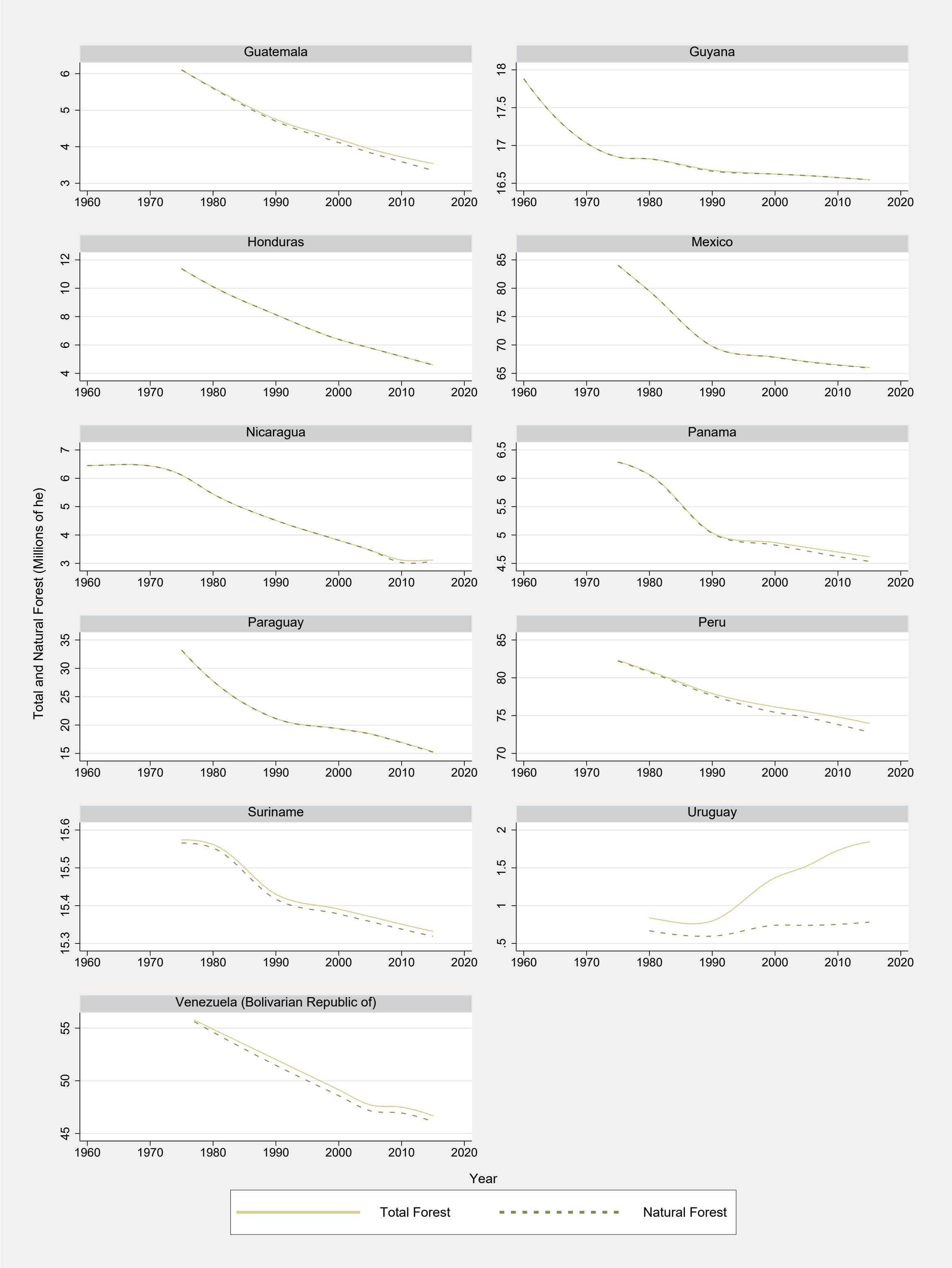
Note: Reconstruction carried out by means of fudge factors.

Figure 2.15 *Latin America: total and natural forest cover (1 of 2)*



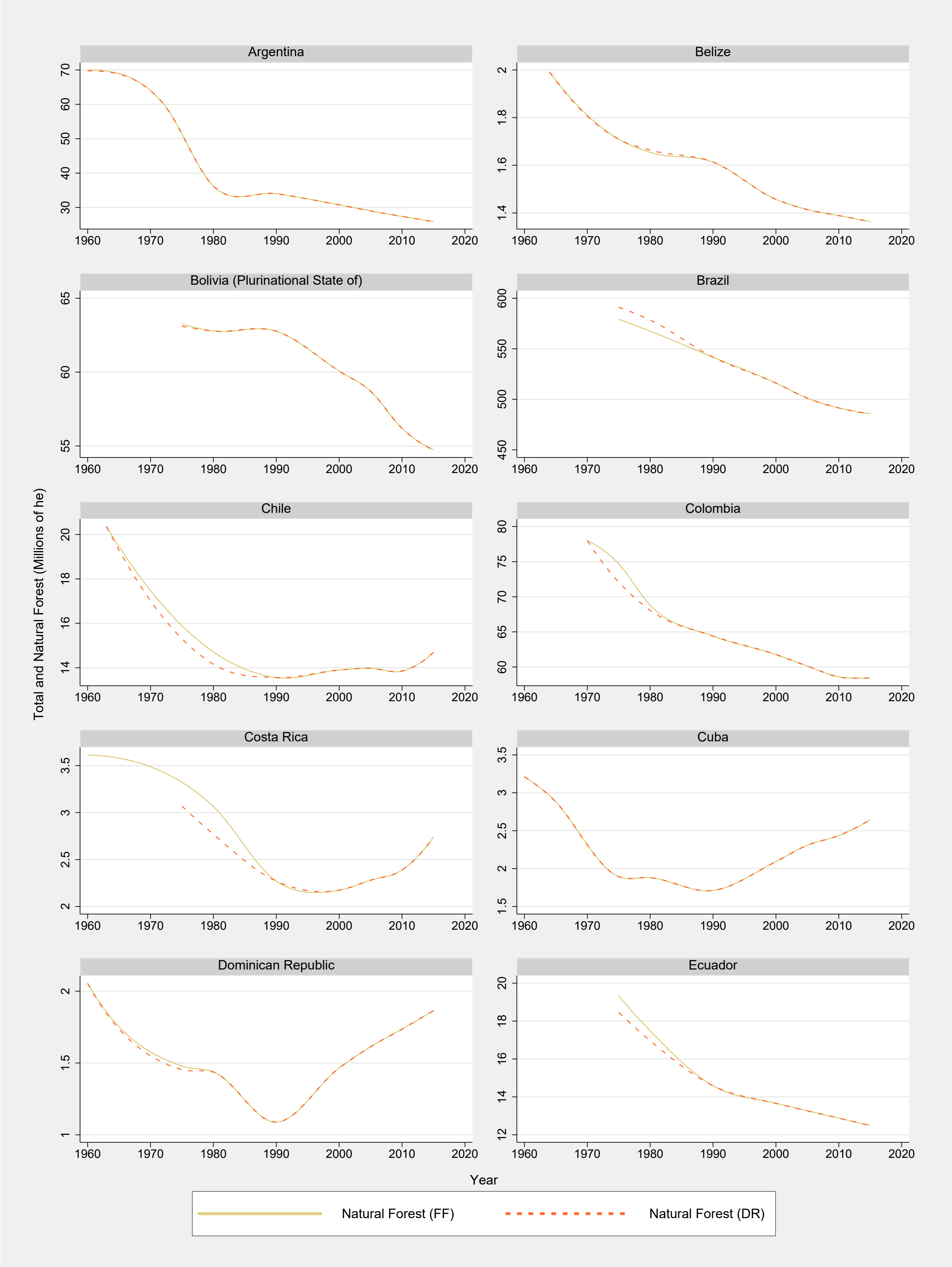
Note: Reconstruction carried out by means of fudge factors.

Figure 2.16 *Latin America: total and natural forest cover (2 of 2)*



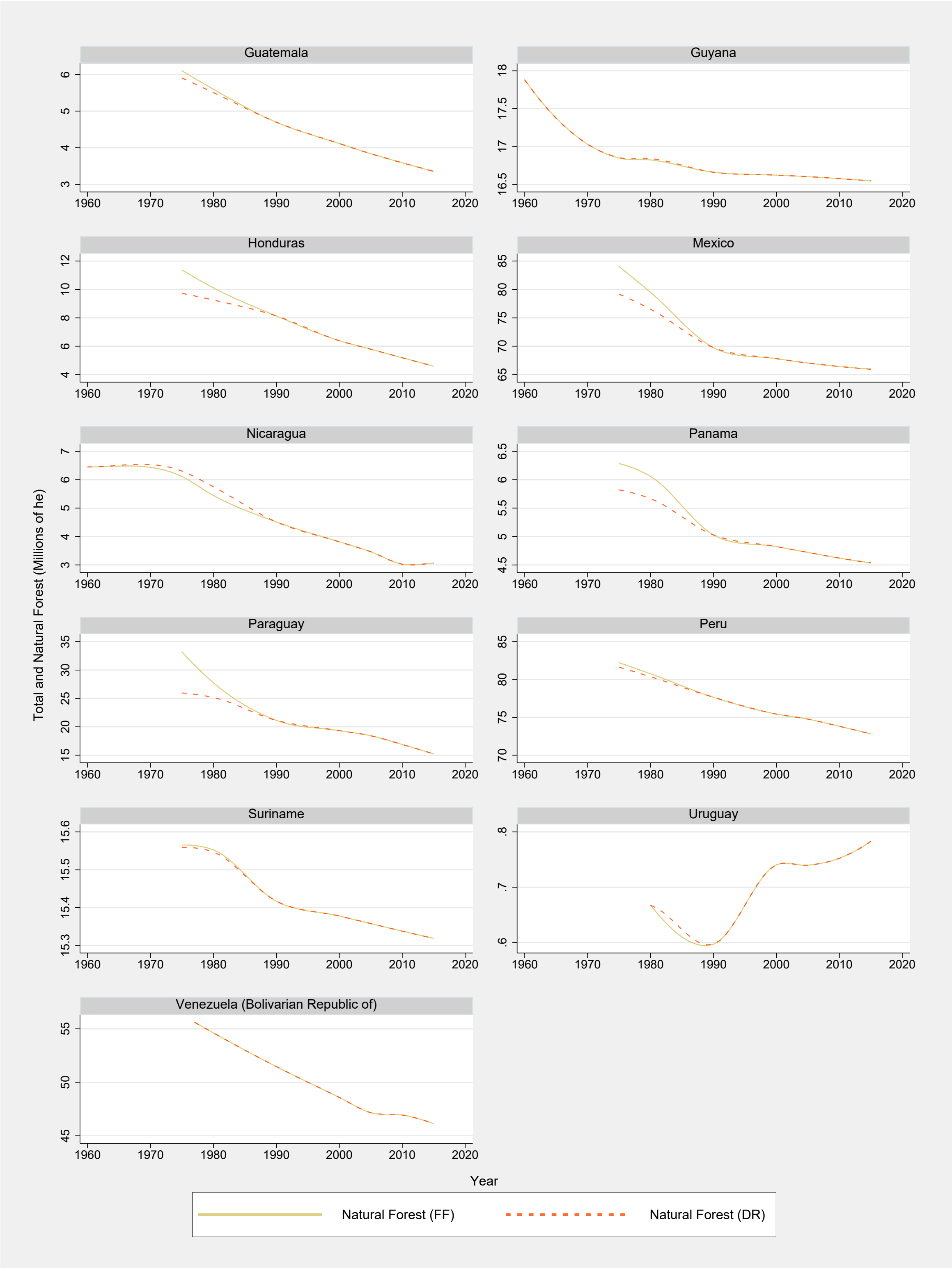
Note: Reconstruction carried out by means of fudge factors.

Figure 2.17 *Latin America: natural forest cover with FF and DR (1 of 2)*



Note: Reconstruction carried out by means of fudge factors and deforestation rates.

Figure 2.18 *Latin America: natural forest cover with FF and DR (2 of 2)*



Note: Reconstruction carried out by means of fudge factors and deforestation rates.

3 The EKC for deforestation

Man is the most insane species. He worships an invisible God and destroys a visible Nature. Unaware that this Nature he's destroying is this God he's worshiping.

Hubert Reeves

AFTER reconstructing forest cover trend in the previous chapter, the analysis moves forward to its final goal to provide a possible answer to the unresolved question of the EKC applied to the case deforestation raised by Hyde (2014) by means of a proper empirical analysis in the light of the broad literature review carried out in the first chapter and the theoretical conclusion deducted from the re-conciliation of the EKCd with the FT and the FDP theories. The analysis here proposed will be conducted by means of panel data techniques through different models with and without the inclusion of additional variables, beside income per capita. Countries will be divided into three different clusters: low, middle, and high income economies since such division would help to place and investigate them along different phases and shapes of the EKCd. Results are undoubted mixed due to the specif model implemented but it seems that for middle income economies it is possible to retrieve a reverse U-shape relationship between deforestation rates and GDP per capita. For high and low income economies a U-shape pattern emerged instead, but with far different implications. In fact, while the former lies in a phase of reforestation, the latter means how deforestation will rise with further development. Therefore, policies must focus in containing the advancement of deforestation for less developed economies and also concentrate in the decreasing phase of the EKCd for the middle income group since the distance between the peak of the curve and the achievement of zero deforestation could require quite lot of time—and then economic advancements—to be reached.

3.1 Basic hypothesis

Before digging into the methodological aspects of this empirical chapter, it would be necessary and wise to step back and retrace the theoretical background which lies under the EKCd as well the FT and the FDP.

During the beginning phases of general economic development, rural areas are characterized by low wages and inhabitants which rely mostly entirely on natural forest resources for their sustenance (phase I of the FDP). At the beginning forests are depleted giving space to agricultural area, but with higher levels of development the value of forest areas rises and so the demand of forest products of the market. Rural wages increase, and total area of depleted forest expands (phase II). However, with further economic advancements, households and rural workers can find alternative employment in other sector of the expanding economics environment. Therefore, they start to be drawn away from the forests. Whereby, despite forest depletion continues to advance, the rate of forest extraction begins to slowdown (phase III and the turning point of the EKCd). During this continuous process the value of forests reaches a level of competitiveness with agriculture to the point that management forest plantations became even profitable helping the process of decreasing deforestation. Eventually, these two processes continue up to a level of zero deforestation (FT). New forest growth now just offsets continued extraction from natural forests and the total forest area and total standing forest volume are in balance. Nevertheless, with further economic advancements, labor opportunity cost away from natural forests continues to rise as well as incentives for more management forests. At the same time, the wealthier regional population starts to demand and protects the non-market resources of all forestland (including the remaining natural forest). In this phase, deforestation rates become negative since forest growth overtakes forest extraction and the total regional forest, measured either in terms of area or standing volume, starts to recover.

It has been shown how both the EKCd and the FT can be easily placed along this development path (FDP). At the beginning, forest losses—which could be represented either by year change of forest cover or rates of change—increase while the total amount of forest cover decreases.[1] Afterwards, during this decrease, a slowdown in forest losses will occur after reaching their peak in the turning point of the EKCd. Going further, with additional economic advancements, the level of forest losses would eventually reach its zero level or rather the so-called forest transition point; whereupon forest losses will turn into forest gains up to a possible saturation point after a consistent forest restoration process.

This brief review of the path of forest use which could be generally retrieved along the history of a general region, needs to be extended to a more general-country level, characterized by several regions and going further to compare them across different countries. Furthermore, this widening process would substitute local wages with a more general indicator of economic growth such as GDP per capita in order to take into account not only the local forest sector but whole nations. Once this basic hypothesis has been proper enlarged the analysis could move to an empirical application which aims to verify the possible existence of an EKC for the case of deforestation.

3.2 A basic model of investigation

As extensively reported in Chapter 1, the EKC hypothesis started to be investigated in the early nineties through cross-country analysis by means of panel data techniques and the literature is still mostly oriented to this approach. Nevertheless, specific country studies could be easily founded, even for deforestation, which implement time-series techniques. The amount of econometric techniques and tools implemented to test this hypothesis are hard to enumerate since it represents one of the most investigated theories in environmental economics. Even in the case of deforestation, different econometric approaches could be easily found but the number of studies and tools are relatively low and scarce. Therefore, since the goal of this chapter is to attempt a re-assessment of the EKCd in the light of previous studies, a cross-country analysis is proposed conducted by panel data techniques rather than specific country studies. Previous works focused their analysis only on developing and tropical countries for several interrelated reasons. First, the main interest of the forestry literature on deforestation is focused on these countries because they are experiencing from long decades this phenomena which seems to be already overcome in most developed countries. Second, the availability of data,

[1] In order to merge within an unique perspective the FDP, the EKCd, and the FP, the assumption of a continuous economic growth over time has been assumed.

especially from FAO, is richer for developing rather than developed countries.[2] Third, the difficulty in comparing forest cover data due to difference thresholds of canopy cover to define forests.[3] Moreover, the common subdivision of countries relies on three macro areas: Africa, Asia, and Latin America while only the work of Joshi and Beck (2016) enlarged the analysis by including OCED countries.

The analysis here proposed differs from previous work of the EKCd's literature for three main reasons. First, forest cover data has been reconstructed in detail to better assess the issue of the EKCd—and the FT as well—that requires long time period to be verified. Second, the change of the "classical" grouping overcoming the regional subdivision in favor of another one based on different phases of development—or rather income levels. Third, the inclusion of industrialized countries in the analysis.

Since the EKC relates a specific environmental degradation with economic growth, the dependent variable, following the first studies on the EKCd is the yearly rate of deforestation (eq. 3.1) implemented by Shafik and Bandyopadhyay (1992) which is the same of the rate proposed by Puyravaud (2003) but with a time lag of one year.

$$Deforestation\ Rate_{it} = log(Forest_{i,t-1}) - log(Forest_{i,t}) \tag{3.1}$$

Therefore, an increase in this value represents a rise in forest losses while a decrease a slowdown in the rates of forest losses. Values in several cases become negative, thus they have to be intended as reforestation rates then with an opposite perspective. The positive aspects in using of this values are twofold. First, since their represent a change and not a physical units, make the analysis across countries feasible and this is presented as a solution to the problem of forests physical stocks' comparison according to Hyde (2012). In fact, despite FRA's guidelines aim to achieve comparable measures of forest cover across countries, FAO has to take the values communicated by the states as they come; therefore, uncertainties of a complete comparisons in physical stock are elevated. The second aspect is strictly related to the previous one. In fact, the use of rates would make theoretically feasible even a cross-country comparison among developed and developing countries.[4]

[2]Most of FAO's FRAs and forestry inventories have been accompanied by studies focused on specific tropical areas (Africa, Asia, and Latin America), and only one focused on European countries (FAO, 1976c).

[3]Starting from FRA 1980 (Lanly, 1982) up to FRA 2000 the (FAO, 2001b) definition was of 20% for developed industrialized countries and 10% for developing countries.

[4]However, the reconstruction of forest cover data conducted in Chapter 2 with fudge factors already attempted to overcome this problematic.

3.2.1 Data preliminary analysis

The analysis considers 114 countries, those with at least 1,000,000 of hectares of total forest cover in 2000, a choice made to reduce heterogeneity across individuals and enhance the comparison among them. The choice to select countries with this threshold of forest cover is commonly applied in the literature (*e.g.* Cropper and Griffiths, 1994) even if the selected reference year is usually 1990. However, in those cases the FAO Production Yearbook was the source of data with 1994 as last available year. In this case, considering that the analysis goes until 2015, the choice of another reference year was necessarily; furthermore, 2000 is the year when the corresponding FRA edition (FAO, 2001b) implemented a common measure among developed and developing countries to account for forest cover making this base-year particularly suitable.[5]

Forest cover data refers to that reconstructed in Chapter 2 based on the latest data provided by the FRA 2015 of FAO and carried out mostly through the use of fudge factors to harmonize data. For the purpose of this study total forest cover (the sum of natural and planted forest) has been considered since is the core variable in all the three theories considered. Concerning the right-hand variables, GDP per capita has been retrieved from the *World Development Indicator* of the WB (2017) since is the source with the widest country coverage.[6]

Countries have been divided into three categories according to their level of development: low, middle, and high income economies. This subdivision, different from a regional clusterization, aims to help in placing and then analyzing countries which approximately lies in a similar section of the EKCd. Low income economies are expected to pose in the left side of the EKCd, along the descending phase of the FT and within phases I and II of the FDP. Conversely, middle income economies should be placed around the turning point of the EKCd and therefore the descending phase of this curve reaching even reforestation levels, thus the achievement of the FT and higher development along the third phase of the FDP. Eventually, high income economies are expected to lie mostly in the negative side of the EKCd, characterized by negative rates of deforestation and around the second theorized turning point of the EKCd, the one which refers to reforestation rates. The division of countries along their development level follows that proposed by the WB (2018b). The low income

[5] A deepen discussion about these choices related to forest cover data could be retrieved in Chapter 2.

[6] Compared with the main alternatives: the *Penn World Table 9.0* (Feenstra and Timmer, 2015) and the *Maddison Project* (Bolt and Zanden, 2014).

Table 3.1 *Descriptive statistics*

Low income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates	791	0.0085896	0.0089148	-0.0309565	0.0628025
GDP per capita (const. 2010 US$)	791	537.5106	248.6725	115.7941	1574.806
GDP per capita (log)	791	6.189739	0.4420183	4.751814	7.361887
GDP^2 per capita (log)	791	38.508	5.469563	22.57973	54.19739

Middle income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates	2,591	0.0050418	0.0119842	-0.0550942	0.0734565
GDP per capita (const. 2010 US$)	2,591	3498.818	3131.673	142.022	20333.94
GDP per capita (log)	2,591	7.768735	0.9326177	4.955982	9.920047
GDP^2 per capita (log)	2,591	61.22269	14.29803	24.56175	98.40733

High income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates	1,180	-0.003543	0.0085327	-0.0661592	0.0218077
GDP per capita (const. 2010 US$)	1,180	27238.92	16720.44	1119.574	91617.28
GDP per capita (log)	1,180	10.00045	0.7077064	7.020704	11.42537
GDP^2 per capita (log)	1,180	100.5094	13.78017	49.29028	130.5392

group is composed of countries with a GNI per capita equal or lower than US$ 1,005 (21 countries). The middle income group by countries with a GNI per capita level between US$ 1,006 and US$ 12,235 (65 countries).[7] Instead, the high income group is composed by countries with a GNI per capita equal or higher than US$ 12,236 (28 countries). Descriptive statistics of the data, following the three-group subdivision, are reported in Table Table 3.1.[8] Each income group is composed of an unbalanced—but continuous—dataset where observations vary from a minimum of 20 to a maximum of 55.

Figs. 3.1 to 3.4 report scatter plots of total forest cover and GDP per capita over the considered time-span 1960-2015. For space reasons countries of the middle income group have been divided between lower- and upper-middle economies. The low income group is clearly characterized by a general declining path of forest cover over time with the exception of Ethiopia and Sierra Leone which recently inverted their trend while other countries such as Nepal are clearly in a lower-

[7] This group comprehend the two groups of lower-middle (from US$1,006 to US$ 3,955) (33 countries) and upper-middle (from US$ 3,956 to US$ 12,235) economies (32 countries) (WB, 2018b).

[8] GDP values have been reported both in effective and logs levels.

bottom part of the transition. However, GDP trends are remarkably mixed since in some countries such as the Democratic Republic of Congo, Liberia, Madagascar, and Niger have an opposite trend over time albeit associated with continuing losses of forest cover. For the middle income group the number of countries which lies in the bottom side of the FT increases as well as those which clearly experienced a reverse trend in forest cover. The number rises switching from the lower- to the upper-middle group. Nevertheless, a great heterogeneity distinguishes this whole middle cluster since countries which show a declining path over time are presented in both sub-groups. Finally, in the high income group, mainly composed by ancient Western-European economies which already achieved their FTs, forest cover trends are generally growing or stationary, but with some exceptions such as Australia, Canada, and South Korea or Estonia and Portugal where a reduction of forest cover occurred only during the last decade.

Eventually, to get a more direct "feel" of the data Figs. 3.5 to 3.8 show the relationship which occurs for each country between deforestation rates and GDP per capita through curves fitted by means of a robust locally weighted scatter plot smoothing (LOWESS) (Cleveland and Devlin, 1988) following a similar graphical proposition of Mazzanti and Musolesi (2013). This is a non-parametric graphical approach which performs a local-linear regression for a specific subsection of observations, repeated for over the span of the variable on the x-axis (the independent variable) (Fan and Gijbels, 1996). The result is an estimated mean function which relates the two variables of interest and could be represented graphically.[9] The amount of observations considered in each local-linear regression is determined by the choice of a specific bandwidth, in this case equal to 0.5. By looking at the graphs, in the low income group trends are quite mixed meaning how the relationship between income and deforestation follows a not clear path. In fact, in this cluster could be found both countries which lies in the left-side of the EKCd, such as Burkina Faso, Chad, and Uganda, as well as countries apparently in the right-side of the curve such as Ethiopia, Nepal, and Sierra Leone. In the middle income group the number of countries which show a more common decreasing path of the EKCd increase and even in the lower-middle subgroup could be found countries which clearly overcome the classical dome of the EKCd flowing under the red line of zero deforestation. This is the case of Bhutan, India, Laos, Philippines, and Vietnam. Furthermore, in the other subgroup of upper-middle income the number of countries which achieved a

[9]The non-parametric approach does not make assumptions about the function of a model, but let the data define the relationship by itself. An introduction to the non-parametric literature could be found in the works of Li and Racine (2007) and Racine (2008).

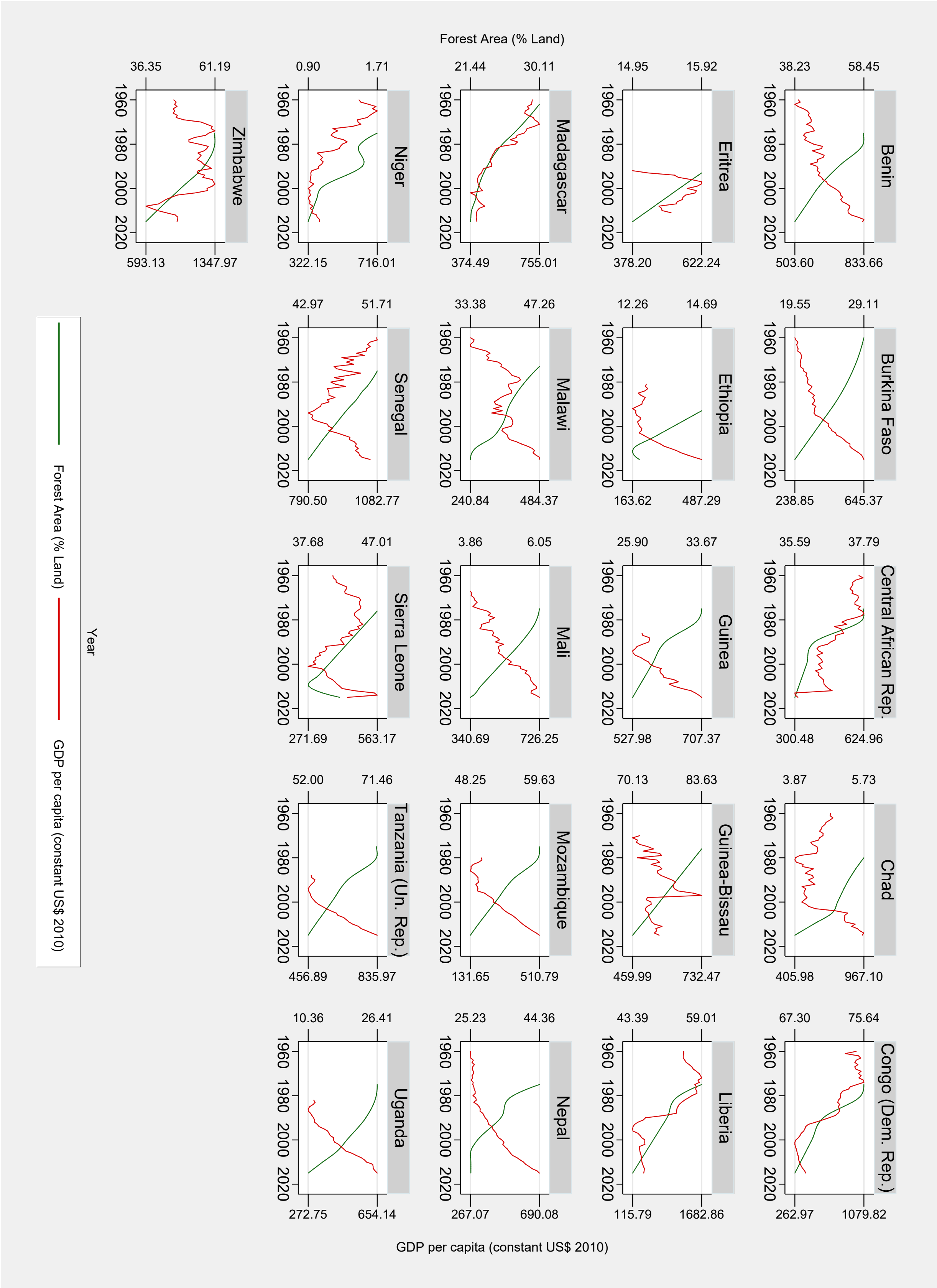


Figure 3.1 *Low income economies: Total forest (% land) and GDP per capita*

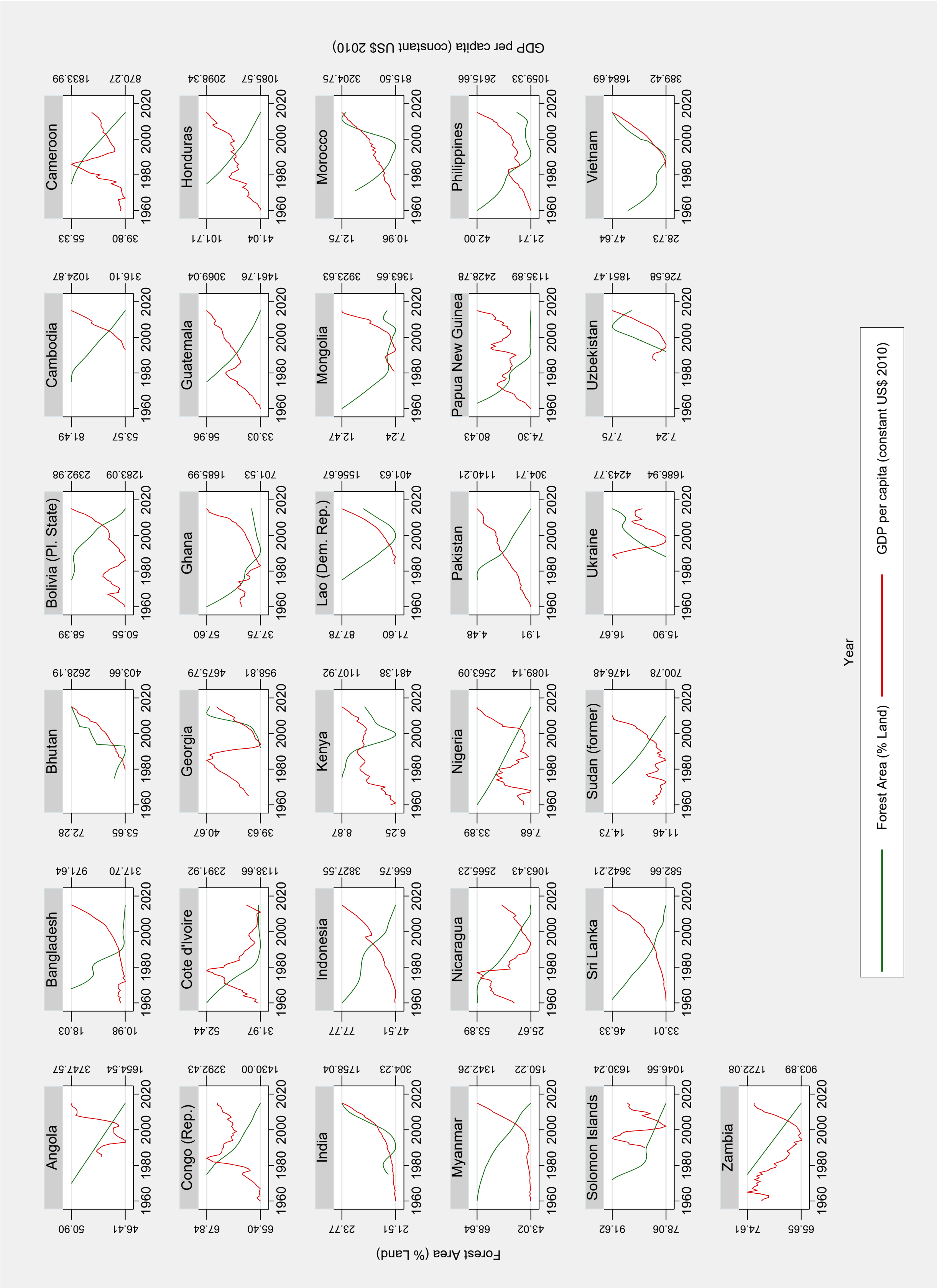


Figure 3.2 *Lower-Middle income economies: Total forest (% land) and GDP per capita*

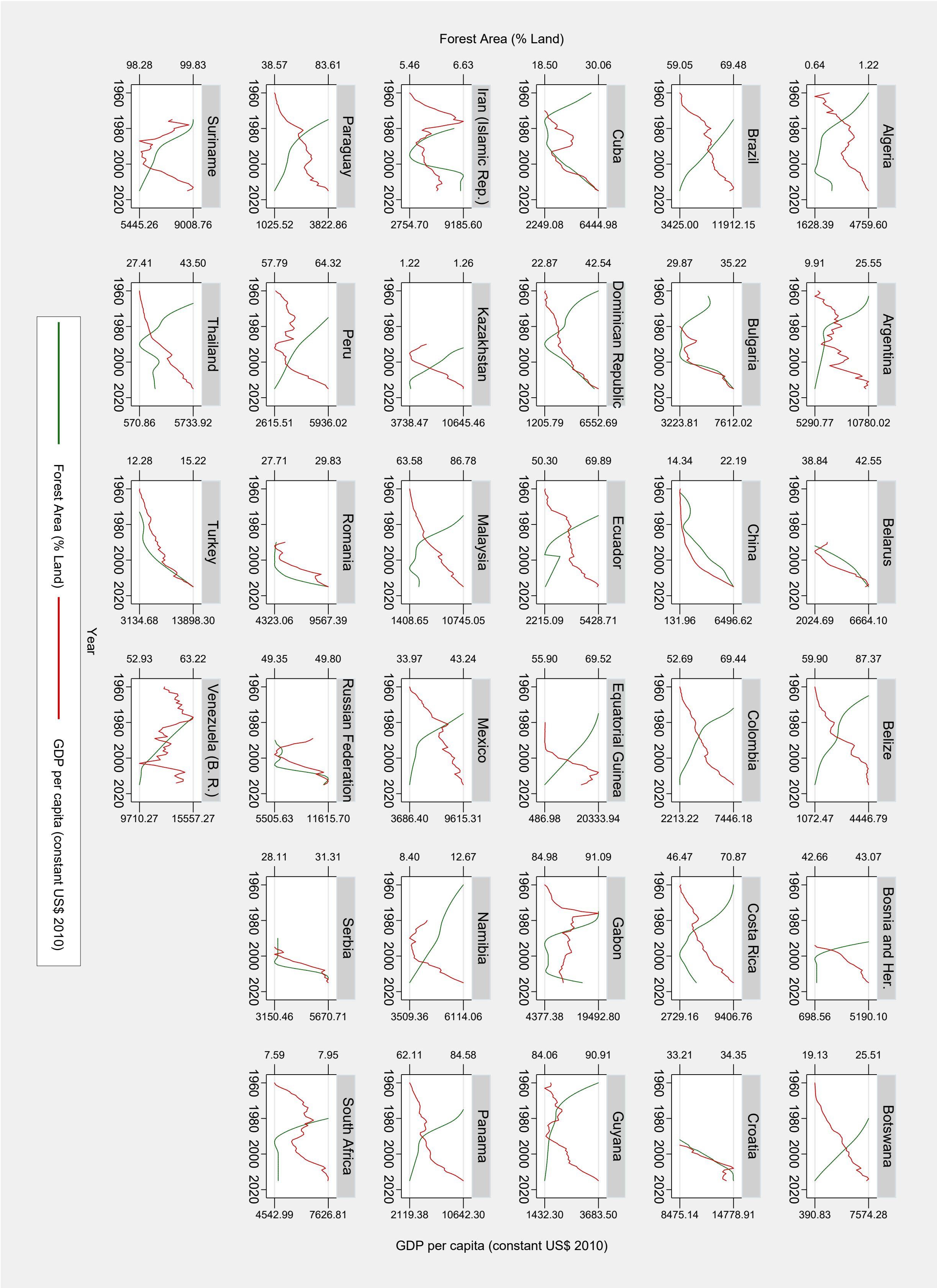


Figure 3.3 *Upper-Middle income economies: Total forest (% land) and GDP per capita*

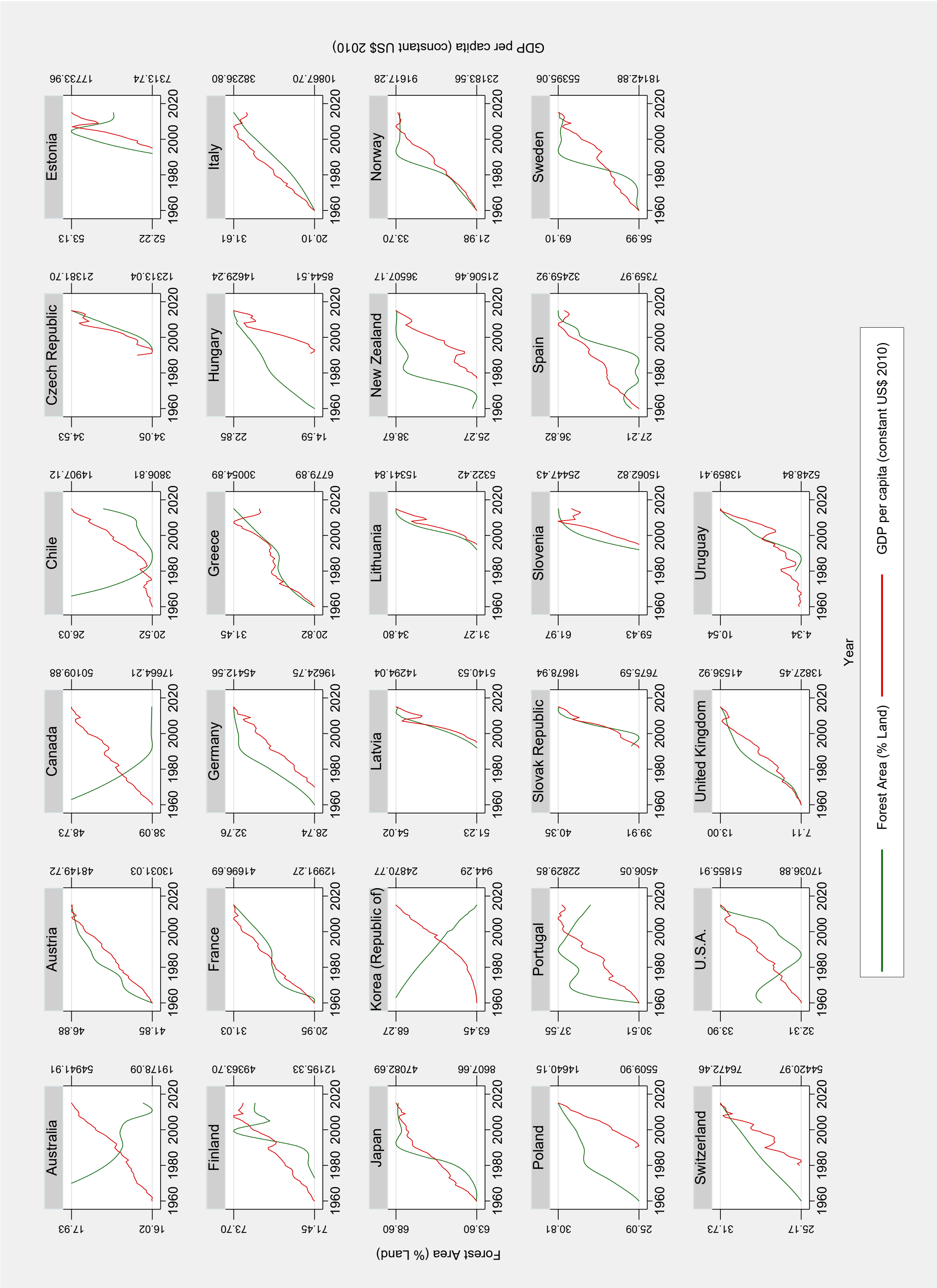
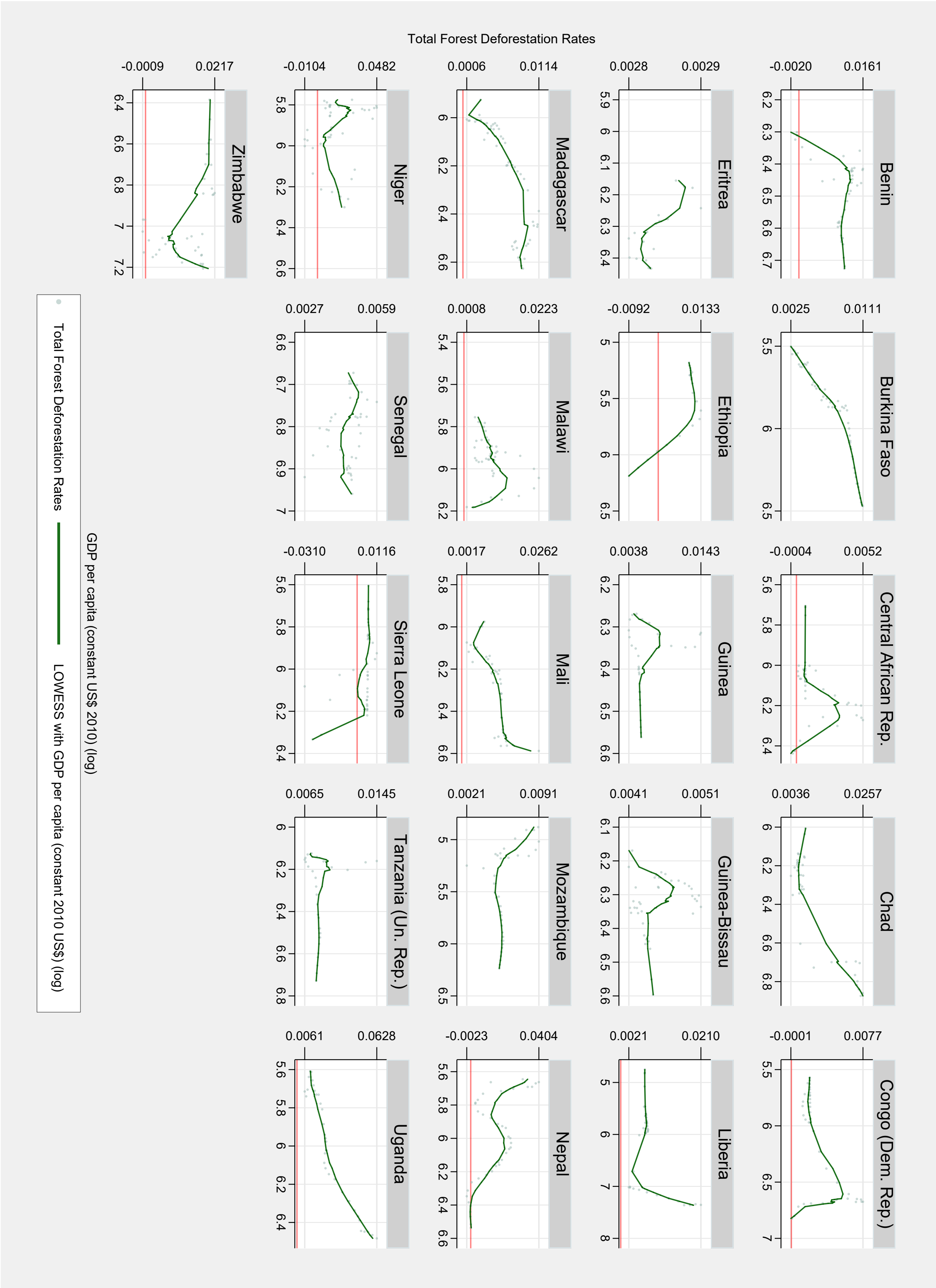


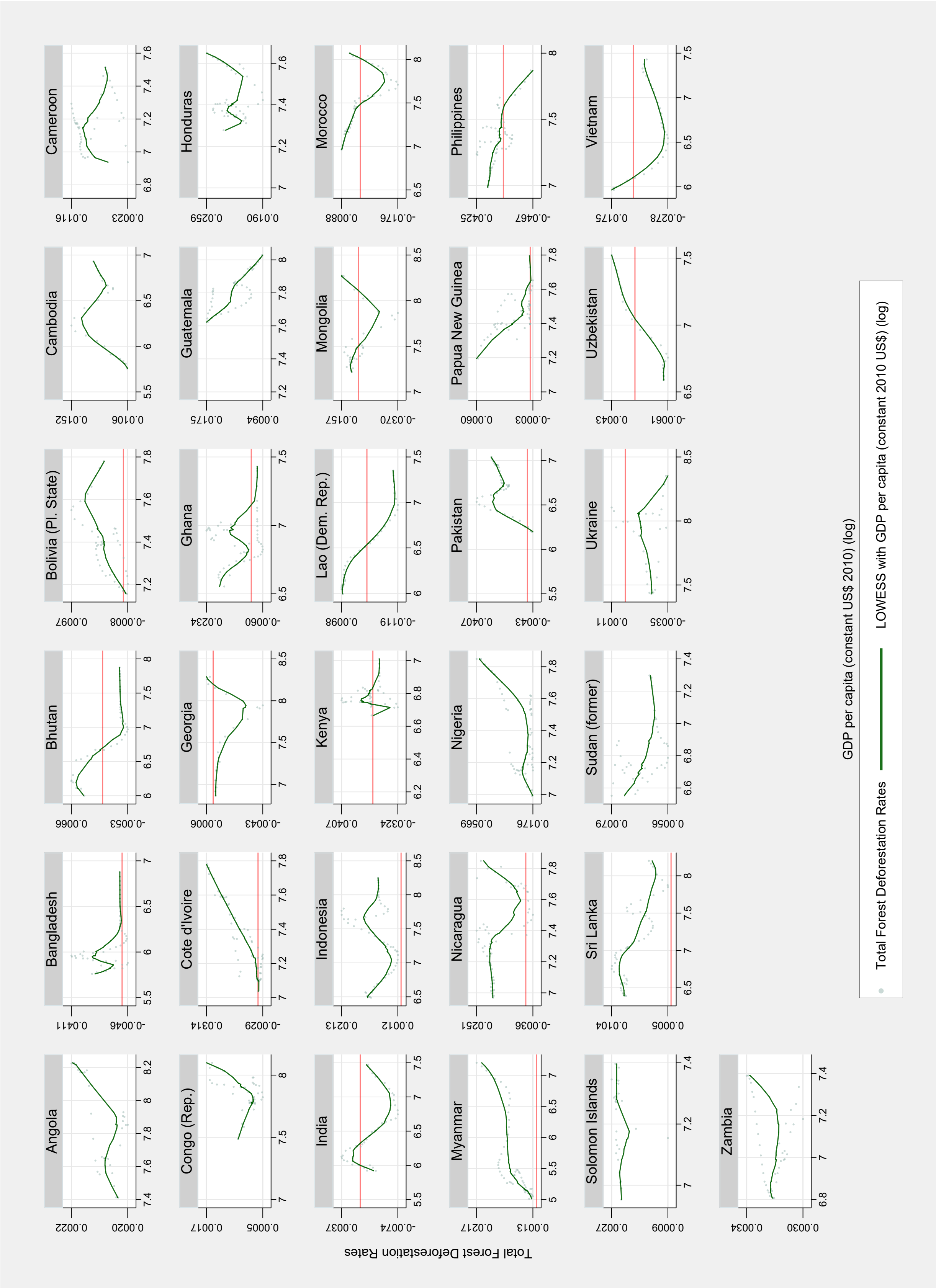
Figure 3.4 *High income economies: Total forest (% land) and GDP per capita*

Figure 3.5 *Low income economies: Total forest deforestation rates and GDP per capita (log)*



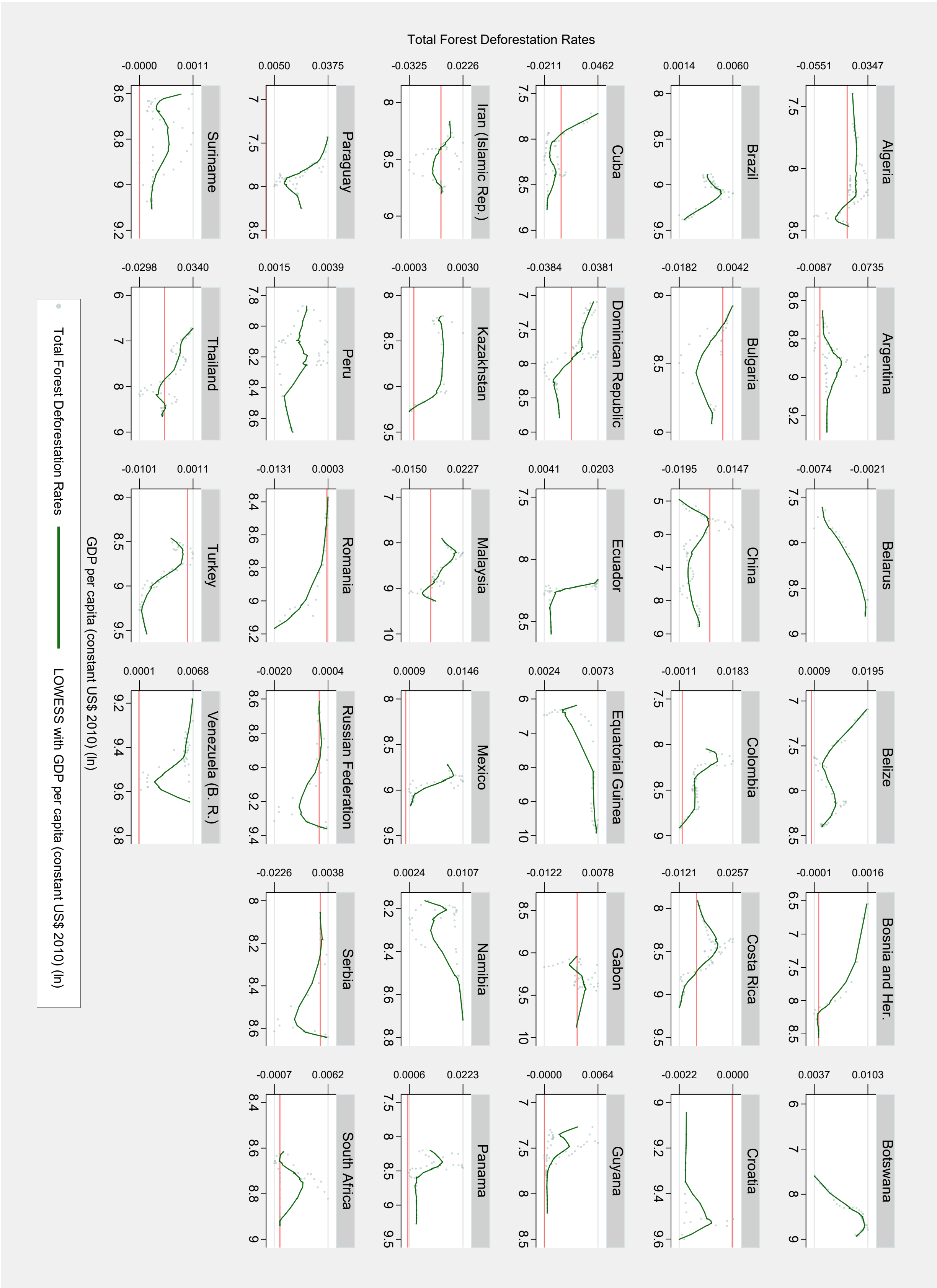
Note: LOWESS function, bandwidth = 0.5. The red line represents the level of zero deforestation.

Figure 3.6 *Lower-Middle income economies: Total forest deforestation rates and GDP per capita (log)*



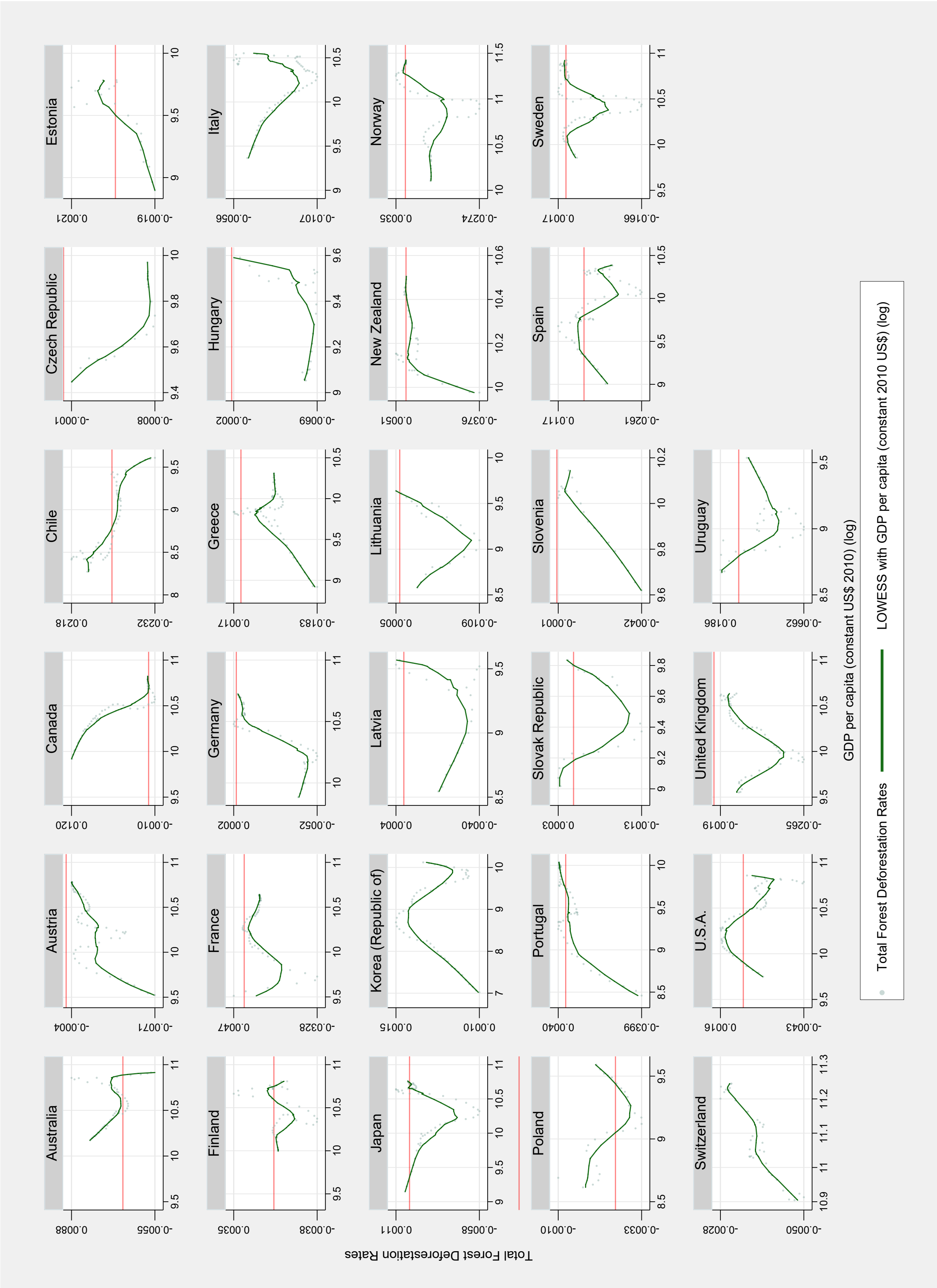
Note: LOWESS function, bandwidth = 0.5. The red line represents the level of zero deforestation.

Figure 3.7 *Upper-Middle income economies: Total forest deforestation rates and GDP per capita (log)*



Note: LOWESS function, bandwidth = 0.5. The red line represents the level of zero deforestation.

Figure 3.8 *High income economies: Total forest deforestation rates and GDP per capita (log)*



Note: LOWESS function, bandwidth = 0.5. The red line represents the level of zero deforestation.

phase of regrowth increase even more. However, the heterogeneity of this group, already evidenced in Figs. 3.2 and 3.3, can be found even with this perspective. In fact some African countries such as Cote d'Ivoire, Equatorial Guinea, and Nigeria show an increasing function, while others have a more oscillating profile both in the ascending and descending side of the EKCd. In the last group of high income economies the second turning point of the EKCd is clearly deduced in the case of France, Italy, United Kingdom, or US. Furthermore, despite some oscillating trend and some slightly return of deforestation rates, those countries could be placed in a general phase of post- or advanced transition.

3.2.2 The model

Following the classical EKC's literature of cross-country analysis, the model proposed to test the EKCd is a panel data with fixed effects which resemble those commonly applied especially in the application for CO_2. This first analysis focused on the basic model with just the dependent variable which represents the environmental degradation (deforestation rate) and the right-hand variable which embody the economic growth of a country (GDP per capita) as showed in the following equation (eq. 3.2):

$$Def_{it} = \alpha_i + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \varepsilon_{it} \tag{3.2}$$

$$t = 1,...,T \qquad i = 1,...,N$$
$$\varepsilon_{it} = \left(0, \sigma^2 \varepsilon\right)$$

Where Def_{it} represents the rate of deforestation for the country i at time t. α_i is the country's specific effect (intercepts in the FE model) which represents those elements or endowments that are not captured by the model and characterize each country without changing over time such as region, climate, and type of forests. Moreover, β_1 and β_2 are the coefficients for the linear and quadratic value of the GDP per capita, respectively. The cubic form has been discarded since the analysis, divided by income groups, is focused on different blocks of the EKCd where a possible N-shape path should be more difficult to retrace considering the analysis' time-span. Furthermore, by adding the cubic term of GDP the analysis would be prone to multicollinearity. Eventually, ε_{it} represents the idiosyncratic error which is assumed to be homoscedastic.[10]

[10]By assuming this specific error structure the model imposes homogeneity among individuals (same variance) or rather absence of heteroscedasticity. Despite the division of the analysis among different income groups for sure reduces the heterogeneity among individuals, this still could be considered as a strong assumption. At the same time this basic model does not take into account possible

The model with just GDP as the only independent variable could rightly rises possible risks of endogeneity in the model—simultaneity between GDP and deforestation rates (*e.g.* Leblois *et al.*, 2017). However, this "risk" can be easily dampened by looking at the work of Lebedys (2004) which investigates the contribution to the forest sector to national economies. Data shows how only Finland presents a relative high percentage of the forestry manufacturing sector's[11] contribution to GDP with 7.6% while other relevant countries have modest percentages: Brazil (4.1%), Cameroon (2.9%), Chile (2.9%), China (1.3%), Indonesia (2.5%), and Malaysia (4.7%). Therefore, considering those values it is possible to "conclude that in all national economies the direct contribution of the forest itself is a small share of the total economy and the contribution of the full forestry sector, including the manufacture of forest products, is hardly large" (Hyde, 2012)[p.229]. In addition, for low and lower-middle income economies, where it could be expected to see an higher contribution of the forestry sector to national income formation, illegal timber activities could actually decrease simultaneously between deforestation rates and GDP per capita. Eventually, those elements allegedly are expected to decrease a possible endogeneity among Def_{it} and GDP_{it} in the model.[12]

3.2.3 Results

The basic model in equation 3.2 provides the relationship which occurs between deforestation rates and economic growth along different income clusters and relative results are reported in Table 3.2. For completeness even the groups of lower- and upper-middle economies are tested as well as a model with only the linear GDP variable. Table 3.2 reports even values related to Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) or Schwarz criterion [13] which are estimator of the relative quality of the model specification (or goodness of fit).[14] Results are significant for all three groups of interest, but for the low income group the significance is only at 5%. The signs for the middle and high income groups are those expected. In the former deforestation rates first increase and then decrease, following the classical reverse U-shape curve of the EKC. In the latter, mostly characterized

flaws related to presence of serial-correlation, cross-sectional dependence, and non-stationarity of the variables. Nonetheless, in the course of this chapter other models will try to relax these assumptions.

[11] With the exception of furniture.

[12] All tests and regressions performed in the following section of this chapter have been carried out with the statistical software STATA 15.1.

[13] The former has been developed in 1974 by Akaike (1998), while the latter by Schwarz *et al.* (1978).

[14] The comparison is conducted between linear and quadratic model.

by reforestation rates, the signs suggest an U-shape path; therefore, reforestation rates first increase (the negative sign, then a decrease of the dependent variable or rather an increase in reforestation rates since values are negative) and then decrease (the positive sign), following the suggested second path of the EKCd after the FT point. Eventually, even for the low-income group results conclude for an U-shape relationship. However, in this case the interpretation is different from the high-income group since these countries are almost completely in a deforestation phase. Furthermore, the high significance of the GDP term in the linear equation suggests a general increasing deforestation path for this group.

After identified the shapes of the EKCd curves for the three income clusters, it is possible to retrieve the respective turning points (TP) through the following equation (3.3):[15]

$$GDP = e^{-(\beta_1/2\beta_2)} \tag{3.3}$$

For middle income economies the TP is reached at the level of US$ 200 per capita which represents the level of income after which deforestation rates start to decrease (or the peak of deforestation rates). Concerning high income economies, the TP is reached at US$ 9,605, when reforestation rates gain their highest value and then start to decrease.

Moreover, by solving the polynomial equation of each income group through the quadratic formula, it is possible to retrieve even the predicted level of zero deforestation which corresponds to the TP of the FT. Regarding the middle income group, the FT is reached with a level of US$ 5,636[16] while for high income economies this level is equal to US$ 1,451. Furthermore, for this group the second solution of the quadratic equation should represents a return in deforestation (a kind of re-switch) with a level of US$ 63,576. However, this remarkably high level of GDP per capita can be observed only in the case of Norway and Switzerland. These results could be explained by the fact that the interpolation methodology could lead to some years of negative forest cover change.[17] Nonetheless, very few observations of the sample lies in this range of "returning deforestation"; then it is possible to assume that reforestation rates could rightly tend over time to a saturation level close to

[15]Considering that GDP terms are expressed in natural logarithms.

[16]The other solution of the quadratic model—which theoretically should represent the beginning side of the EKCd and the FT—is equal to US$ 7 of GDP per capita, a value obviously out of the sample. Nevertheless, considering that forest depletion starts at the very beginning of the development of a society—despite here the concept of GDP is hardly applicable—, it could be assumed to be quite low; therefore, the obtained result assumes a "feasible" value.

[17]For example, this occurs in the case of Norway despite all interpolated values show increasing amounts of total forest cover.

zero. Nonetheless, despite it could be assumed a saturation level of reforestation in a long-term perspective, relative temporary shocks in the path of the EKCd—then periods when the rates of deforestation overwhelm those of forest gains—could occur even for high income economies. For example, in recent years Portugal is experiencing a decrease in forest cover due to the government decision to reduce eucalypti plantations due to avoid to turn the country into a "Eucalyptugal" and because of the overspread of forest fires (The Economist, 2017).[18] Eventually, for low income economies the TP occurs at US$ 283 but the solution of the polynomial leads to imaginary solutions meaning that the curve cannot reach a level of zero deforestation, thus the FT. In fact, despite some exceptions, this group is mostly characterized by countries whose rates of deforestation are always positive (no reforestation) then this justifies the absence of a real solution or rather the TP of the FT.[19]

Table 3.2 provides further information showing data even for lower- and upper-middle income countries. In their quadratic specification there is a general lack of significance in the variables while their linear models show in both of the cases negative and significant coefficients, higher for the upper-middle groups, as expected. This means that both group seem to experience a general decrease in deforestation rates over time. However, only by considering the whole group of middle income seems possible to identity the EKCd specification. Finally, by looking at the linear model of low, middle, and high income economies, results and coefficients' significance are substantially in line with a general EKCd approximation: increasing deforestation rates for low income, decreasing for middle income, and decreasing reforestation rates for high income economies.

3.2.4 Discussion

Starting from the results showed in Table 3.2, it is possible to attempt a graphical representation of the predicted values of Def_{it} over GDP_{it} to give a visual idea of this relationship. Figure 3.9 shows the predicted curves for low, middle, and high income economies derived from the coefficients in Table 3.2. The curve for the middle group is mostly composed of a decreasing path since the TP of the EKCd is reached at the very beginning with a relative low level of GDP per capita. This

[18]According to Oliveira *et al.* (2017), forest fires represent an endogenous factor which negatively affects the FT's path of Portugal.

[19]Furthermore, by comparing AIC and BIC of linear and quadratic functions, the difference is quite small meaning how the quadratic approximation does not represents a remarkably better model specification.

Table 3.2 *EKCd model with FE*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0333**	0.00299***	0.00244	-0.00284***	0.0123***	-0.00506***	0.00998	-0.00622***	-0.0255***	0.00107**
	(0.015)	(0.001)	(0.009)	(0.001)	(0.004)	(0.000)	(0.007)	(0.001)	(0.007)	(0.001)
GDP^2	0.00295**		-0.000382		-0.00116***		-0.00104**		0.00139***	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
Constant	0.101**	-0.00991*	0.00874	0.0269***	-0.0197	0.0444***	-0.00637	0.0557***	0.112***	-0.0142***
	(0.045)	(0.005)	(0.030)	(0.005)	(0.017)	(0.004)	(0.026)	(0.005)	(0.032)	(0.005)
Observations	791	791	1,267	1,267	2,591	2,591	1,324	1,324	1,180	1,180
AIC	-5608.4	-5604.1	-8477.9	-8479.5	-16914.1	-16900.2	-8462.5	-8458.4	-8405.3	-8390.7
BIC	-5594.3	-5594.8	-8462.5	-8469.3	-16896.5	-16888.5	-8446.9	-8448	-8390.1	-8380.6

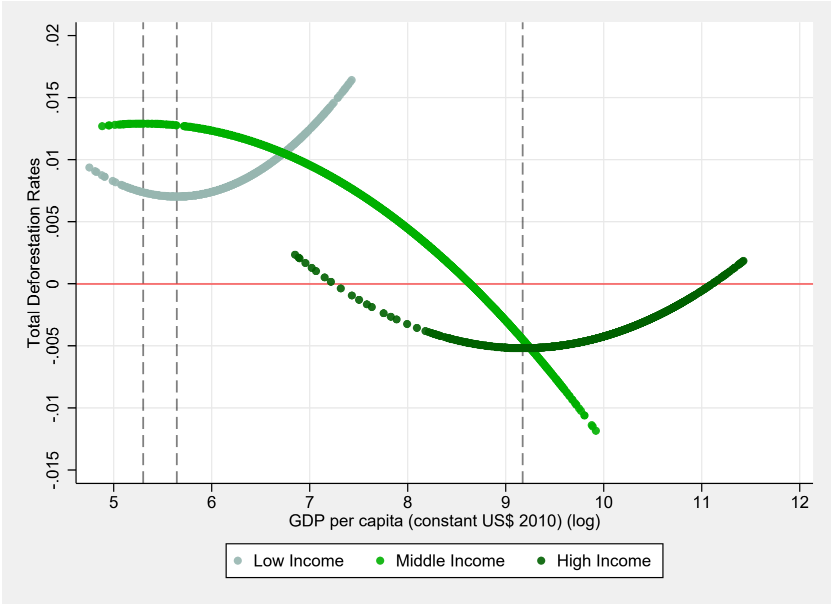
Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

means that those countries mostly lie in the declining phase of the EKCd while low income economies rise their rates after the peak of the middle income group. Several aspects can help to understand this U-shape relationship between deforestation and GDP for these countries. Some countries have been—or still are—afflicted by long periods of turmoil and civil wars during which the depletion of forests could be either spurred or reduced. Some fragile economies show medium-to-long periods of decreasing GDP per capita which does not necessarily corresponded to a return in forest cover—a backward movement along the speculated FT curve—since the natural growth rate of forest cannot follow slavishly that of economic.[20] Moreover, illegal timber activities results in an increase of deforestation not necessarily—or directly—reflected in an increase of GDP. However, regarding this last aspect, it is possible to identify it as a common risk that countries in phase I and II of the FDP could face due to low property rights or high costs to secure them. Going further along the FDP it is reasonable to expect an increase of the general level of institution, boundaries control, and certification of forest products.[21] Another

[20]The initial side of the EKCd for this group could be explained by the fact that several countries along the considered time-span experienced a reduction of GDP over time followed by a related reduction in deforestation rates. However, since these two values are not expected to evolve strictly together, some exceed of deforestation reduction with relative low income levels could lead to an initial path of decreasing deforestation rates (Niger, for example, is one of the countries which shows this behavior).

[21]The matter of certificated forest products is particularly widespread in developed countries. The total amount of certified forest area in 2017 amounted to 429 millions of hectares, mostly located in the north hemisphere. Countries members of the United Nations Economic Commission for Europe (UNECE) host 85% of total certified forest while only 15% can be found in the combined area of Africa, Latin America, Asia, and Oceania (UNECE and FAO, 2017). Therefore, along the EKCd, countries which lies in the decreasing phase of the curve, especially during the regrowth phase of the FT, are expected to embrace practices of forest certification. Furthermore, by imposing specific labels to forest products—which must come from forest that meet Standards of Forest Management (SFM), more developed countries are able to disincentive illegal timber market from less developed partners. The certification of forests area are likely to shift downward on the right the curve to secure property rights in the scheme of the FDP similar to what showed in Figure 1.24. However, there are

Figure 3.9 *Predicted values of the EKCd model*



Notes: The horizontal red line represents the level of zero deforestation. Furthermore, the three vertical dotted lines correspond to the TPs for middle, low, and high income economies, respectively.

explication could be the occurrence of a net displacement effect where wealthier countries (in the lower- or upper-middle group)—that have undertaken a process of deforestation reduction—substitute the internal demand of primary forest products by importing them from less developed countries. By doing so GDP levels for low income economies would increase hand in hand with a boost in deforestation rates. Eventually, population growth, agricultural expansions, and lack of institutions are for sure aspects which highly affect the use of forests in low income countries.

The TP of the EKCd appears to be quite low, especially if compared with other results obtained in the literature (see Table 1.1). Nevertheless, it should be remembered that the peak of the curve represents the maximum level of forest loss per year reached by a country and during the declining phase this still represents a phenomena which—eventually—slowly fades away before reaching the regrowth phase of the FT—and the period which divides those two phase is reasonably long. At global level, in the last 25 years the net loss of forest cover decreased from 7.4 millions of hectares per year over the period 1990–2000 to 3.3 in 2010–2015. In the middle income group changes moved from 5.8 in 1990–2000, 2.7 in 2000–2005, and 1.5 millions of hectares per year in 2005–2010. However, during the following five

even negative aspects related to forest certification. For example, for small-producers in developing countries it is ofter hard and costly to obtain certifications and thus these commitments are perceived as an imposition from developed countries (Ahmad, 2018).

years (2010–2015) a new return in deforestation occurred with 3,9 millions of hectares losses per year (FAO, 2015). This behavior for sure could be ascribed in part to the occurrence of the global financial crisis which pushed a return in the depletion of forest resources or by the fact that some countries, such as China, reached their negative side of the EKCd and started to slacken their regrowth phases. Therefore, it is reasonable to hypothesize that globally a great number of countries are experiencing a decreasing phase in the EKCd and it is not a recent tendency. Undoubtedly, it cannot be imagined that all countries fit within the obtained TPs (especially for middle income economies) since Figs. 3.2 and 3.3 showed how the behavior changes within and between income groups.

Asia: China and Vietnam

Several examples can easily fit these results and this apparent low TP (around US$ 200). For example China, which clearly experienced remarkably efforts and results in the reforestation process, started policies of forest plantation and conservation since the foundation of the People's Republic of China in 1949 to face soil erosion and flooding (Li, 1998; Zhang *et al.*, 2000), and in 2003 started the fourth phase of the ambitious project aimed to build a Green Belt Wall (through the Three-North Shelter Forest Program, started in 1978) in order to stop the advancement of the Gobi desert (Liu *et al.*, 2009).[22] In addition, Hyde *et al.* (2008) identified the level of rural income at which natural forest switches from net losses to gains at ¥ 563 (approximately US$ 64), a level achieved in mid-1980s. Even the work of Zhang *et al.* (2006) reached similar results showing how 21 out of the 31 China's provinces reached the increasing phase of the EKCd in 2001[23]

Vietnam can represent another example of a country which experienced both the EKCd's TP as well as the FT with relative low GDP levels. This country registered high rates of deforestation during the seventies and eighties, but starting from the beginning of the nineties reforestation rates overtake deforestation rates and the FT eventually occurred. At that period Vietnam registered an average GDP level of US$ 550 per capita,[24] but the declining phase of its ECKd begun further

[22]However, results of this project are debated (*e.g.* Wang *et al.*, 2010; Tan and Li, 2015). In addition, even the process of plantation is questioned since in Southwestern China it is implemented as monocultures—then with low diversification from a biological point of view—and results to be associated with a displacement of native forests (Hua *et al.*, 2018).

[23]Both Hyde *et al.* (2008) and Zhang *et al.* (2006) used total area as dependent variable on the vertical axis of their EKCd rather than deforestation rates.

[24]Data about the corresponding GDP per capita level in this section are retrieved from WB (2017) and expressed in constant 2010 US$.

before. Vietnamese governments implemented specific forest-protection policies throughout these years of transition protecting natural forests while enchanting the overspread of fast-growing plantations (Meyfroidt and Lambin, 2009). In addition, forest products exported moved from raw roundwood toward processed wood with high value-added retracing what suggested by Hyde (2012).

The cases of China and Vietnam for sure represent two of the most rapid transitions, but literature recognize how it occurred at the expense of a displacement of deforestation to other countries, the leakage effect commonly traceable in the EKC literature of CO_2. Meyfroidt and Lambin (2009) evidenced how in the Vietnamese case 39.1% of this regrowth turned into a displacement of forest products to neighborhood countries, a leakage effect occurred mostly in the form of illegal timber trade, especially from Cambodia and Laos. China like Vietnam is another country whose market is characterized by processed forest products relying in the import of basic roundwood since log activities are severely restricted.[25] The most vibrant market in this perspective is the one of valuable tropical timber species, mostly from Indonesia, Malaysia, and Papua New Guinea (Chunquan *et al.*, 2004; Schloenhardt, 2008). Furthermore, some researches claim how almost 80% of total imports of forest products in China is illegal (Stark and Cheung, 2006; Laurance, 2008).

In the Asian group other examples of countries that achieved their FT could be found (Mather, 2007). India is another country whose FT occurred during the eighties driven by agricultural intensification,[26] government policies, and smallholders community based activities (Singh *et al.*, 2017). When the FT achieved its TP, India's GDP per capita was around US$ 500. Moreover, Bhutan is counted as another example in this plethora, where the FT occurred during the 2000s after a period of substantially stable forest cover change due to increased trade liberalization and a transition from shifting cultivations to a more market-oriented agricultural sector (Bruggeman *et al.*, 2016). In the year 2000 the GDP per capita of Bhutan amounted around US$ 1,200.

[25]China in 2016 was the major country in the import of several forest products, mostly primary: industrial roundwood (39%), sawnwood (23%), pulp for paper (33%), and recovered paper (50%) (FAO, 2018).

[26]Started in the sixties during the so-called Green revolution it is not always assessed in the literature as a phenomena which actually incentivized forest restoration (Foster and Rosenzweig, 2003).

Latin America

Moving to the Latin America group, these countries are generally placed in the phase III of the FDP (Hyde, 2012) and it is not a case that the Central America sub-group is placed by Redo *et al.* (2012) in a general regrowth phase along their FT-development curve. Chile and Costa Rica are the two main examples of countries which experienced a clear FT in Latin America. Chile's transition occurred during the eighteens and after 1986 (US$ 4,972) a continuous growth of forest cover has been registered by Heilmayr *et al.* (2016). This path has been primarily driven by the overspread of fast-growing and high-productive plantations such as eucalyptus and radiata pines, an old "tradition" started in the middle of the last century (Haig, 1946) but even enhanced by investments in forestry research (Sedjo and Botkin, 1997). Other drivers are represented by government afforestation subsidies and trade openness (Niklitschek, 2007). In the case of Costa Rica the period when the effective transition occurred is debated: while the common government orientation places it around the beginning of the nineties, another study (Sierra *et al.*, 2015), carried out through satellite images, show how the TP is fairly recent, approximately around 2005. Therefore, the corresponding GDP level at which the transition occurred should range between US$ 4,500 and US$ 6,800. Trade openness and declining prices of meat in the international market represented two aspects which favored the transition in Costa Rica (Daniels, 2009). In addition, a liberalization process spurred restoration and protection activities, especially on private forestlands mixed with a growing ecotourism phenomena (Kull *et al.*, 2007), certainly favored by the fact that 25% of the territory is composed by protected area (SINAC, 2018). Going further in this regional group, even Cuba and Dominican Republic, clearly reached their turnaround along the FT curve (*e.g.* Rudel *et al.*, 2005, Meyfroidt and Lambin, 2011) while others, such as Brazil, are still in their declining phase of the EKCd—evidenced by the decreasing rates of deforestation occurred after 2010 in the Legal Amazon area (INPE, 2017)—but not yet close to the switch from forest losses to gains.

Africa

Concerning African countries, they are mostly concentrated in the low income group experiencing continuous decreasing forest cover area, especially in the Sub-Saharan region. However, in some cases deforestation rates started to decrease or even revert, such as the cases of Ethiopia and Sierra Leone. In the case of Ethiopia, in the Southwest area of the country deforestation occurred mostly in remote areas while regions more integrated with city markets are associated with less deforestation since they can offer better off-farmer jobs (Getahun *et al.*, 2013). Even community-based forest management activities driven the decrease in deforestation rates for Ethiopia (Takahashi and Todo, 2012). According to FAO's data, the transition in these countries occurred in between 2010 and 2015, with an average GDP per capita of US$ 400 and US$ 500, respectively. However, most African countries are characterized by fluctuating GDP trends derived for example by civil wars or droughts with undeniable repercussions in the pressure on forest resources. Moreover, African countries are generally associate by Hosonuma *et al.* (2012) to a pre- or early-transition phase in the tropical area, while an early- or post-transition in the Savannah area. Therefore, despite the African's paths along the FT are mixed, with some cautions it could speculated that some countries are experiencing the decreasing phase of the EKCd or even its negative side. Eventually, it must not be forgotten the fact that planted forest activities in tropical developing countries not necessarily are recent phenomena since they could occur even in early stages of development promoted by governments with the goal of erosion control (Hyde, 2012). For example, in Malawi forest plantations date back in the late twenties and a government statement of 1964 stressed out the importance of plantations in the protection of fragile areas, water supply, biodiversity, and the ensure of self-sufficient forest production (MFFEA-FD, 1992; FAO, 2010d).

The identified TP of the EKCd, despite apparently low (US$ 200), when compared to specific cases seems to be quite reasonable, thus deforestation rates start to decrease at relatively low levels of GDP and then the FT falls into a range which spans from US$ 1,458 to US$ 5,636. Furthermore, moving to a more historical analysis; France, for example, reached its FT between the revolution of 1789 and 1862. The first available data for GDP per capita is of 1820, when it was presumably equal to US$ 1,442 while in 1862 it was equal to US$ 2,432. In the case of Hungary the TP of the FT occurred in 1925 when the GDP per capita was equal to US$ 1,650.[27] These two examples, retrieved from the work of Mather (1992) with historical GDP data provided by (Bolt and Zanden, 2014) fit inside the range of the FT. Therefore, since the FT in several cases turns out to fit within the identified range—or even before, it is not unlikely to imagine a relative low TP for the EKCd because it occurs far before the FT. Obviously, the GDP in this framework represents a proxy able to catch countries' economic development and not the leading factor which drives

[27] These data for GDP are expressed in constant 2011 US$.

Table 3.3 *Heteroscedasticity: Modified Wald test*

	Low Income	*Middle Income*	*High Income*
Chi^2	3.70E+06	3.70E+06	3.70E+06
Prob > Chi^2	0.000***	0.000***	0.000***

Notes: Modified Wald test for groupwise heteroskedasticity. H_0 = no heteroscedasticity, $\sigma(i)^2 = \sigma^2$ for all i. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively.
The test has been performed on the model in the equation 3.2.

deforestation and/or reforestation processes. During each phases of development different factors come to the fore changing the function of forest values as suggested by the FDP. At the very beginning of a society, forests represents the main—if not the first—natural resource depleted; therefore, the EKCd starts before other more "common" Kuznets' indicators and thus its peak occurs before and probably is even more empirically traceable rather than pollutants.

3.2.5 A robust estimation

The model performed in equation 3.2 assumed homoscedastic errors. However, this represents a strong assumptions which could lead to biased results. Therefore, in this section the possible presence of heteroschedasticity, serial-correlation, and cross-sectional dependency among the income clusters will be tested. Eventually, a proper robust estimator will be implemented trying to control for heteroschedasticity, serial-correlation, and cross-sectional dependency.

The issue of heteroscedasticity rises when there is heterogeneity among individuals and the errors have the same variance since they are assumed to be independent from the right-hand variables. However, despite the income clusterization performed, it would be hard to assume homogeneity among countries within the income groups. In fact, the Wald test proposed by Greene (2002)[28] refuses in all the cases the null hypothesis H_0 of no heteroscedasticity as showed in Table 3.3.

Conversely, serial-correlation (or autocorrelation) arises when values of a variable are influenced by previous observation and then determined by them. This is a relevant issue, especially for forest data, since the interpolation methodology implemented for the reconstruction could undoubtedly lead to a past-dependency of forest cover data and consequently on deforestation rates as well. To investigate the possible presence of serial correlation the test proposed by Wooldridge (2010) is performed for the model. Results in Table 3.4 show how in all cases the null

[28]This is a modified Wald test for groupwise heteroscedasticity conducted in the residuals of a FE regression model.

Table 3.4 *Serial-correlation: Wooldridge test*

	Low Income	*Middle Income*	*High Income*
F	16,092.96	4,918.57	5,224.42
Prob > F	0.000***	0.000***	0.000***

Notes: Wooldridge test for autocorrelation. H_0 = no first order autocorrelation. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. The test has been performed on the model in the equation 3.2.

Table 3.5 *Cross-sectional dependency: CD test*

	Low Income			*Middle Income*			*High Income*		
	Def_{it}	GDP_{it}	GDP_{it}^2	Def_{it}	GDP_{it}	GDP_{it}^2	Def_{it}	GDP_{it}	GDP_{it}^2
CD test	2.16	9,85	9.94	25.1	171.82	172.82	3.07	108.87	108.8
p-value	0.03**	0.000***	0.000***	0.000***	0.000***	0.000***	0.002***	0.000***	0.000***
corr	0.026	0.119	0.12	0.086	0.607	0.611	0.033	0.933	0.932
abs(corr)	0.466	0.551	0.552	0.514	0.682	0.685	0.446	0.933	0.932

Notes: H_0 = Cross-section independence CD ~$N(0,1)$. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively.

hypothesis H_0 of no first-order autocorrelation is reject in favor of the presence of serial-correlation in the model.

Eventually, cross-sectional dependency arises when individuals are not assumed to be independent but rather to influence each other so that covariances are not assumed to be equal to zero (contemporaneous dependence among individuals). This intra-individuals correlation may arise for several reasons, such as global or regional shocks (*e.g* financial or oil crises) but also due to spillover effects. In the case of the EKCd this correlation could probably arises even due to timber trade activities and the possible net displacement of deforestation from one country to others (*e.g.* Meyfroidt and Lambin, 2009; Meyfroidt *et al.*, 2010). If ignored, the possible presence of cross-sectional dependency in panel data techniques could lead to biased results. Therefore, the CD test of Pesaran (2004) is implemented for each variable of each group. The null hypothesis H_0 of cross-sectional independence is rejected in all cases as showed in Table 3.5.

Once identified these flaws which affect the FE model presented, the same estimation in equation 3.2 is performed with Driscoll and Kraay (1998) robust standard errors.[29] In fact, this estimation is robust to heteroscedasticity, serial-correlation, and cross-sectional dependency. Results are reported in Table 3.6.[30] The general result is of a slightly loss of significance in the coefficients, especially in the middle income group. However, since the predicted values of this group showed

[29]The original estimator proposed by Driscoll and Kraay (1998) considered only balanced panel. For STATA, Hoechle (2007) adjusted the estimator for unbalanced panels as well.

[30]The values of AIC and BIC are not provided by this estimator.

Table 3.6 *EKCd model with FE (Driscoll and Kraay robust standard errors)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0333*	0.00299***	0.00244	-0.00284*	0.0123*	-0.00506***	0.00998	-0.00622***	-0.0255**	0.00107
	(0.017)	(0.000)	(0.012)	(0.002)	(0.007)	(0.001)	(0.009)	(0.001)	(0.012)	(0.001)
GDP^2	0.00295**		-0.000382		-0.00116**		-0.00104*		0.00139**	
	(0.001)		(0.001)		(0.000)		(0.001)		(0.001)	
Constant	0.101*	-0.00991***	0.00874	0.0269**	-0.0197	0.0444***	-0.00637	0.0557***	0.112*	-0.0142
	(0.054)	(0.003)	(0.045)	(0.012)	(0.027)	(0.006)	(0.036)	(0.008)	(0.058)	(0.009)
Observations	791	791	1,267	1,267	2,591	2,591	1,324	1,324	1,180	1,180

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. The maximum lag order considered for the autocorrelated structure is 3.

(Figure 3.9) how prominent was the decreasing side of te EKCd, this aspect remains significant, both in the linear specification and the squared GDP coefficient (negative) of the quadratic model. Regarding the low income group, similar—but opposite—to the middle group, the positive coefficients are those with the higher significance. Eventually, in the high income group as well the U-shape curve is significant at 5% while is not in the linear formulation. Nonetheless, it must by noticed how in the lower-middle group both quadratic and linear specification result not significant differently from the upper-middle income group. Therefore, when the model takes into account heteroscedasticity, serial-correlation, and cross-sectional dependency, despite some loss in significance, the functional form of the EKCd continues to hold.

3.2.6 A wider perspective: all income economies

The model presented rightly clustered countries according to their income levels trying to reduce their heterogeneity and thus conduct a more accurate analysis of the phenomena. The idea was to study countries which presumingly could be placed in different sections of the EKCd. However, limitations could arise from this approach since along the period of investigation countries moved from one cluster to another. Moreover, the robust estimation in Table 3.6 showed how the EKCd shape for middle income economies lost significance when the model controlled for heteroscedasticity, serial-correlation, and cross-sectional dependency. Therefore, a more direct and wider analysis could be easily conducted simply removing any kind of clusterization and thus by testing the whole sample. Table 3.7 shows the results of the FE conducted for the 114 countries of the panel. Since now all economies are considered at the same time, it does make sense to add even the cubic term of GDP to equation **??**. Results show of AIC and BIC confirm a better goodness of fit for the cubic model rather than linear and quadratic. The coefficients of this model are all significant at 1% and the signs are those expected: first a positive relationship (the increase of deforestation), then a decrease (the decreasing side of the EKCd), finally a new increase but reasonably related to negative deforestation rates (the second turning point of the EKCd, after the FT). Moreover, even estimation with Driskoll and Kraay robust standard errors are reported and results remain significant.

Trying to deepen the analysis, the same model has been performed even for natural forest with the aim to inspect if different results would occur.[31] In the literature of the EKCd only one study (Motel *et al.*, 2009) considered data for natural forest, primarily due to a general lack of data. However, the reconstruction carried out in the previous chapter provides a consistent amount of data to carry out this analysis. The expectation is to obtain a similar EKCd curve but substantially shifted to the top right respect to the horizontal axis. In fact, when considering total forest cover, deforestation rate—which are mostly related to the depletion of natural forest—could be remarkably softened by the rise of managed forest plantation (for example eucalyptus, characterized by fast growth rates) especially during the phase III of the FDP. Therefore, the effective peak of the EKCd would be lower due to the presence of plantation and moving further to the right, the achievement of the FT for natural forest will be delayed compared to total forest. In fact, when the net forest depletion is equal to zero and continue with positive gains, the depletion of natural and old growth forests will continue even if with lower rates. This occurs because part of the population continues to rely on marginal areas or has not yet moved to other job opportunities and also because, depending on tree species, some of them still remain of high value for the market (legal or not), thus there is still an incentive to rely on primary forest goods from natural forest rather than non-market goods.[32] Results in Table 3.8 show how the cubic specification even in this case is preferred to the others according to AIC and BIC values. Also the coefficients are all significant—both in the simple and robust FE estimation—with the same signs of the previous cubic model meaning how even natural forest generally follow the same global path of total forest.

Among the countries mentioned as examples in Section 3.2.4 which clearly showed a FT in the last decades, only few of them experienced a return in natural forest cover and only at national level since some specific case studies affirm the

[31] Descriptive statistic for this variable is reported in Appendix A (Table A.1).

[32] It must be recalled the possible limitation that could rise when comparing forest data from both developed and developing countries due to differences in past FAO's inventories in the definition of forest cover for these two groups (Cropper and Griffiths, 1994). Nonetheless, this limitation has already been overcome by te reconstruction provided in Chapter 2 and by the fact that the dependent variable is expressed in rates rather than total amount (Hyde, 2012).

Table 3.7 *EKCd model with FE for total forest (all income economies)*

Def (total forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.00258***	-0.00258***	-0.00640***	-0.00640***	0.112***	0.112***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.012)	(0.015)
GDP^2			0.000242*	0.000242*	-0.0149***	-0.0149***
			(0.001)	(0.001)	(0.001)	(0.000)
GDP^3					0.000621***	0.000621***
					(0.000)	(0.000)
Constant	0.0243***	0.0243***	0.0388***	0.0388***	-0.262***	-0.262***
	(0.003)	(0.005)	(0.008)	(0.009)	(0.030)	(0.038)
Observations	4,562	4,562	4,562	4,562	4,562	4,562
AIC	-30625.5		-30627.1		-30735	
BIC	-30612.6		-30607.8		-30709.3	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

contrary.[33] However, this is completely in line to what predicted by the FDP. In fact, the overwhelm of losses in the open access forests could be achieved only if each kind of forest is considered, thus especially planted forests.[34]. Therefore, when the FT occurred is highly possible if not foregone that natural forests will continue to decrease for some time before switching into a regrowth phase. Results from this basic model confirm this.

Considering the results from the two cubic specifications, it is possible to retrieve the turning points of the EKCd for natural and total forest by resolving the cubic formulation. Regarding the former, the EKCd peak is reached at US$ 502.7 while the second at US$ 41,773; in the latter the peak is equal to US$ 415.7 while the second TP to US$ 20,952. Moreover, the FT is reached at US$ 2,345 for total forest and US$ 7,555 for natural forest.[35] The higher TPs (as well as the FT) for natural

[33]While Meyfroidt and Lambin (2011) identify Bhutan, Costa Rica, China, and Vietnam as countries where the FT occurred even for the category of natural forest, Hua *et al.* (2018) in the case of China and Heilmayr *et al.* (2016) for Chile—which could be ascribed to the group of countries that registered a net increase in natural forest cover, especially during the period 2010–2015 (FAO, 2015)—show cases of forest plantation expansion occurred to the detriment of natural forests, at least for some time. Furthermore, as for Costa Rica, while data from the last FRA 2015 (FAO, 2015) shows how both primary and natural forest increased over the period 2000–2015, data provided by Sierra *et al.* (2015) in 2013 still registered losses in the category of *bosque maduro* (mature forest).

[34]Hyde (2012) enlarges this view suggesting how all kind of tree should be considered (even those which grows on roadsides or in some backyards) referring to a measure of tree cover and not forest cover.

[35]The second solution from the cubic formulation provides the FT level for the two models. Furthermore, the other two solutions could be interpreted as the level at which the depletion of forests starts and the re-switching point, thus a possible return of deforestation for high income levels (when the EKCd curve crosses the horizontal axis from below). Concerning the first solution,

Table 3.8 *EKCd model with FE for natural forest (all income economies)*

Def (natural forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.00484***	-0.00484***	0.00754	0.00754	0.117***	0.117***
	(0.001)	(0.001)	(0.006)	(0.007)	(0.032)	(0.031)
GDP^2			-0.000805**	-0.000805	-0.0149***	-0.0149***
			(0.000)	(0.001)	(0.004)	(0.004)
GDP^3					0.000589***	0.000589***
					(0.000)	(0.000)
Constant	0.0434***	0.0434***	-0.00223	-0.00223	-0.276***	-0.276***
	(0.007)	(0.010)	(0.022)	(0.024)	(0.082)	(0.077)
Observations	4,424	4,424	4,424	4,424	4,424	4,424
AIC	-21471.2		-21474		-21484.3	
BIC	-21458.4		-21454.8		-21458.8	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

forest evidence how the EKCd is shifted to the right, as predicted. Furthermore, the graphical representation of the predicted functions in Figure 3.10 provides a more clear evidence of the two curves and how natural forests, without considering forest plantations, reaches a higher peak of the EKCd, a higher FT, and even a more delayed and less pronounced second turning point in the negative quadrant.[36]

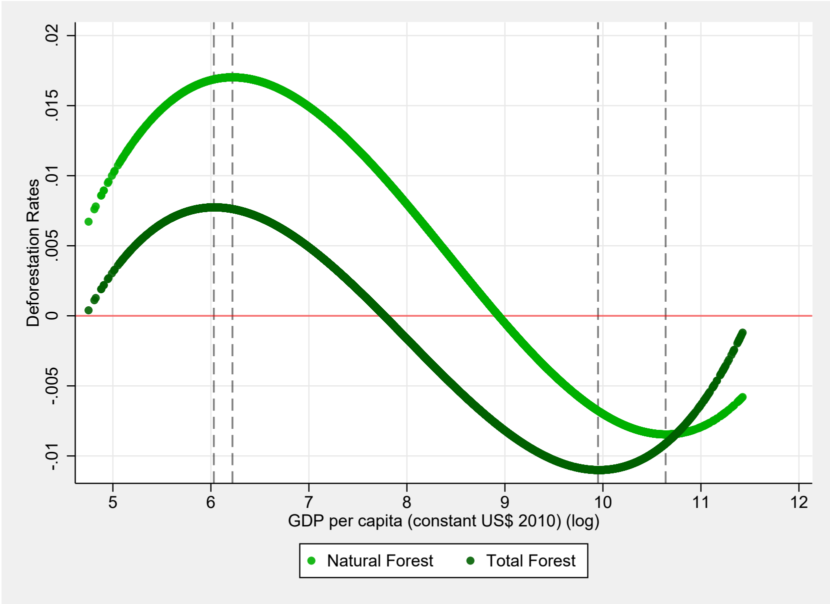
3.3 An enlarged model

Once defined the possible existence of an EKCd when only the two main variables are considered (environmental degradation and economic growth), the analysis could be enhanced by including additional control variable in the regression. In fact, while the literature of the common EKC is mostly focused on the simple relationship between CO_2 and GDP with a scant use of additional control variables,

for natural forests it is equal to US$ 79.04 while for total forest to US$ 112.17. Concerning the third solution of the cubic formulation, it is equal to US$ 98,715 for total forest and US$ 159,98 for natural forests. However, in the sample there are no countries with such high income levels.

[36]The same model for natural forest (without the cubic term) has been performed even for the different income clusters. Results, reported in Appendix A (Tables A.2 and A.3), are generally in line with the expectations, then some slight resemblance with the EKCd. The U-shape relationship for low income economies persists even in this model but with a lower TP (US$ 217). In the middle income group results show no evidence of a particular shape but rather a negative coefficient. Eventually, even for the high income group the U-shape form is preserved, with an higher TP and FT level (US$ 31,160 and US$ 9,509, respectively). However, coefficients are significant only with the basic model but not with the robust estimation.

Figure 3.10 *Predicted values of the EKCd cubic model (all income economies)*



Notes: The horizontal red line represents the level of zero deforestation. Furthermore, the three vertical dotted lines correspond to the TPs for total and natural forest.

the deforestation side of the literature is far more generous from this perspective, even too plentiful.

There is a vast literature which attempts to investigate the main drivers of deforestation, especially in tropical countries, but conclusions are not always aligned to a common consensus (*e.g.* Angelsen and Kaimowitz, 1999; Geist and Lambin, 2002; Culas, 2009; Rudel *et al.*, 2009; Angelsen and Rudel, 2013; Pfaff *et al.*, 2013; Ferretti-Gallon and Busch, 2014). Following Busch and Ferretti-Gallon (2017), drivers could be grouped into four macro groups: First, biophysical characteristics, such as elevation, which represents an obstacle to harvest activities (access costs and distance from the markets). Second, the presence of infrastructures and the proximity of urban areas and roads which incentive the access and the depletion of forest resources. Third, agriculture and timber activities and prices where the former are commonly associated with an increasing deforestation while the impact of the latter is more uncertain. Fourth, demographic and socioeconomic variables where population is commonly associated with more forest losses but the relationship between forest cover and poverty seems to show mixed results. Lastly, institutional variables, ownership and management rights whose impacts are generally positive or uncertain in reducing deforestation.

Another classification, first proposed by Angelsen and Kaimowitz (1999), identifies three groups of causes: *underlying*, *intermediate*, and *direct causes* of deforestation.

Within this last group there are the direct actors or primary agents of deforestation: farmers, pastoralists, and wood collectors. Furthermore, even commercial agents play a major role with logging activities, extensive agriculture or infrastructures developments (*e.g.* hydropower power plants).[37] The decisions of primary agents are directly influenced by the intermediate causes such as agricultural (input and output) and timber prices, property rights, and credit access. At the top of this structure there are the underlying or indirect causes that comprehends macro-level factors and policy-oriented instruments such as market and policy failures, economic and population growth, Structural Adjustment Programmes (SAPs), and export orientation. Eventually, to these three groups even another one could be added relatively to *natural* (or man-induced) *causes* (*e.g.* hurricanes, natural fires, floods, wars, and global warming) (Culas, 2009).

Within this rich literature is also configured the EKCd hypothesis and for this reason it is usually enriched by the inclusion of additional control variables aimed to identify drivers which affect—both positively and negatively—deforestation. However, the risk is to fall into a so-called "kitchen-sink" regression where all kind of possible independent variables, directly or indirectly related to deforestation are implemented to explicate the response variable of deforestation rates. Among the plethora of possible additional variables, four of them have been selected: agricultural area, population density, trade openness, and a proxy for institutions. The choice to narrow the amount of control variables was also needed due to data availability. Therefore, only variables able to avoid an excessive shrink in terms of N and T of the panel dimensions has been selected. Descriptive statistics for these variables, divided in each income group, are showed in Table 3.9.[38]

Agricultural expansion undoubtedly represents the first cause of deforestation. Both crops and livestock are presented in this category accordingly to FAO's definition.[39] It is expected to have a direct relationship between agricultural expansions

[37] Usually these two categories of primary agents are defined as "the needy and the greedy" where farmers represent the former while commercial agents the latter (Culas, 2009).

[38] Values are expressed in effective and logs levels.

[39] Agricultural variable is composed of the sum of three elements. Arable land: "the land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). The abandoned land resulting from shifting cultivation is not included in this category." (FAO, 2017a). Permanent crops: "the land cultivated with long-term crops which do not have to be replanted for several years (such as cocoa and coffee); land under trees and shrubs producing flowers, such as roses and jasmine; and nurseries (except those for forest trees, which should be classified under "forest") (FAO, 2017a). Permanent meadows and pasture: "the land used permanently (for a period of five years or more) for herbaceous forage crops, either cultivated or naturally growing. A

Table 3.9 *Descriptive statistics for additional control variables*

Low income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Agriculture (% Land)	762	0.4015698	0.1721439	0.0786542	0.7516832
Agriculture (log)	762	-1.036601	0.5534363	-2.542694	-0.2854404
Population Density (% Land)	762	0.4461413	0.420838	0.0330918	1.989097
Population Density (log)	762	-1.231986	0.9726995	-3.40847	0.6876806
Trade Openness (Imp + Exp % GDP)	762	55.38262	27.18369	14.31728	311.3553
Trade Openness (log)	762	3.932392	0.3884143	2.661467	5.740934
Institutions	762	-0.9317585	5.491656	-9	9
Institutions (log)	762	2.122501	0.6541717	0.6931472	2.995732

Middle income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Agriculture (% Land)	2,386	0.3933576	0.1971575	0.0037821	0.8398131
Agriculture (log)	2,386	-1.15668	0.8655828	-5.577489	-0.1745759
Population Density (% Land)	2,386	0.7908301	1.342154	0.0111581	12.36811
Population Density (log)	2,386	-1.029323	1.328088	-4.495589	2.515121
Trade Openness (Imp + Exp % GDP)	2,386	70.18115	45.23304	0.1674176	531.7374
Trade Openness (log)	2,386	4.050143	0.7249824	-1.787264	6.27615
Institutions	2,386	1.217938	6.74354	-10	10
Institutions (log)	2,386	2.266606	0.7738194	0	3.044523

High income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Agriculture (% Land)	1,160	0.4062187	0.2309778	0.0245315	0.8600731
Agriculture (log)	1,160	-1.181619	0.8933924	-3.707798	-0.1507379
Population Density (% Land)	1,160	1.070866	1.11327	0.01684	5.193303
Population Density (log)	1,160	-0.626174	1.380458	-4.083998	1.64737
Trade Openness (Imp + Exp % GDP)	1,160	61.04384	32.4345	8.929523	184.3277
Trade Openness (log)	1,160	3.976017	0.5343735	2.189363	5.216715
Institutions	1,160	8.501724	4.172716	-9	10
Institutions (log)	1,160	2.913834	0.4278293	0.6931472	3.044523

and forest losses during the phase I of the FDP, thus a positive impact of the variable on deforestation, especially for low income economies. During phases II and III of the FDP the relationship between land intended to agricultural purposes and forest losses is no longer direct since an area of degraded land can occur between these two

period of five years or more is used to differentiate between permanent and temporary meadows" (FAO, 2017a).

categories and the value of forest land rises to a level where the woody material is required in the market and forest are not representing just an "impediment" for further agricultural expansions. Therefore, the impact of agricultural areas on deforestation would expect to be positive even for middle income economies, but less pronounced considering the whole time-span of the panel. Regarding high income economies, those generally show a decrease over time of the area dedicated to agriculture giving space to a natural regeneration of forests. Whereby, a no particular significant relationship is expected for them. The variable is expressed as agricultural area over total land area in logs and values are retrieved from FAOSTAT (FAO, 2017a).[40]

Population is considered another driving factor of deforestation since it embodies the pressure on natural resources applied by the expansion of societies. A positive relationship is expected between population and deforestation during the first phases of development, hence for low income economies. Moving to middle and high income economies, the impact of population it would expect to decrease since higher incomes increase the opportunity cost of other activities away from the forest sector and the process of urbanization, by reducing the amount of rural population, can therefore reduce the overall impact on forest depletion. According to Templeton and Scherr (1999), population pressure initially increases deforestation but, after a certain rate of growth, it leads to a conservation of the considered natural resource. Within the EKCd literature, the presence of a population variable is widely used both in terms of growth or density starting from the work of Grossman and Krueger (1995). For this study this variable, retrieved from the WDI database (WB, 2017), is expressed as population density (total population over land area) in logs. The expected sign is positive for low income economies with a slowdown effect for middle and more industrialized countries.[41]

[40]This variable agricultural area, would allow to account even—if only partially—of the so-called land grabbing phenomena. Overspread after the world food price crisis of 2007–2008, land grabbing is characterized by large-scale of land acquisition by transnational companies, governments, and private investors in the Global South with the aim to covert them into sites for food and fuel production but also for water and mineral control. Within this global framework are involved not only North countries but also South actors in what, for its features, is often ascribed as a form of "neo-colonialism" (Borras Jr *et al.*, 2011; Cuffaro *et al.*, 2013). Therefore, since these land acquisitions usually include vast forest areas, the rise of the variable agricultural area due to land grabbing (for example, in favor of extensive crop or palm oil production) is linked with the dependent variable of deforestation rate.

[41]Nonetheless, the use of a population variable with FAO data provided by FRA 1990 has always been avoided due to possible endogeneity among EKCd's studies since the so-called "deforestation model" (see section 2.2) implemented in this assessment to predict deforestation for several tropical countries considered population growth in its formula. However, since the reconstruction has been carried out by means of FFs, with the use of different FAO's sources whose data have been all reconducted to the most recent FRA 2015, it is reasonable to believe that the effect of this kind of endogeneity is less pronounced.

Trade openness and in general an economic liberalization have a positive association with deforestation for Angelsen and Kaimowitz (2001) even though this relationship is conflictual and not utterly defined. In fact, Hyde (2012) claims how a freer trade and technological improvements are two conditional factors able to reduce the critical (economic) point at which forests start to recover. Several examples could be found in te literature. For example, Foster and Rosenzweig (2003) showed how economic growth rates are associate with positive forest growth rates only for economies with relative closed markets. On the contrary, in the case of Chile's transition, trade openness is considered as one of the leading factors (Niklitschek, 2007). Following Leblois *et al.* (2017), trade openness is represented as the sum of import and export as percentage of GDP (WB, 2017), expressed in logs, and the expected sign is undefined.

Eventually, institutions have a key role in the depletion and preservation of natural resources, for example, in the literature of the so-called resource curse hypothesis (*e.g.* Bulte *et al.*, 2005). Better institution are generally associated with a better use of natural resources and preservation of them. However, since it is hard to identify possible variables able to catch countries' level of institution over a considerable long time span, it is necessary to use a proxy.[42] Therefore, the variable *polity* provided by the project *Polity IV* of the Integrated Network for Societal Conflict Research (INSCR, 2017) has been selected to fulfill this task. Values of this variable range between -10 and +10 meaning complete authoritative or democratic governments, respectively. In order to express the values in logs terms, this variable has been previously reshaped with values which span from 1 to 20. Therefore, the assumptions is that an higher level of democracy is generally associated with better institutions, even if this represents a cautious assumption.[43] This variable is expected to affect negatively the deforestation levels. Nonetheless, this variable has to be used cautiously since it tends to have a low variability over time, especially for

[42] Probably one of the most comprehensive indicator of institutional variables is represented by the *Country Policy and Institutional Assessment* database of the WB (2018a). This source is composed by a list of 21 discrete variables which span from the rate of property rights and rule-based governance to the one of gender equality. Unfortunately, the country coverage of these variables is limited as well as the time series which actually spans only from 2005 to 2016 (however, in a previous version of these data the coverage dates back to 1996). Another good set of variables able to provide a good proxy for the level of institution of a country is the *International Country Risk Guide* of the PRS Group (2017) which provides country-risk data dividend into 12 different indicators over the period 1984-2016 for 140 countries. Nonetheless, despite the quite good time coverage of these variables, they do not provide a full country coverage and have no free-access.

[43] Another similar variable is represented by the sum political rights and civil liberties provided by Freedom House (2016), first used by Torras and Boyce (1998) in the EKC's literature and then by Bhattarai and Hammig (2001) in the case of deforestation.

Western countries. Therefore, when performing a panel FE, this variable is wiped out for several individuals. Aware of this possible limitation, the model proposed in this section will be performed with and without the use of this additional control variable.

The enlarged model is showed in the following equation 3.4 where the basic model (eq. 3.2) has been enhanced with the additional variables previous described. The same assumptions of the basic model have been made concerning the idiosyncratic error.

$$Def_{it} = \alpha_i + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \beta_3 Agr_{it} + \beta_4 Pop_{it} + \beta_5 Trd_{it} + \beta_6 Ins_{it} + \varepsilon_{it} \quad (3.4)$$

$$t = 1,...,T \qquad i = 1,...,N$$
$$\varepsilon_{it} = \left(0, \sigma^2 \varepsilon\right)$$

Where, in addition to the basic variables of the EKCd, Agr is the control variable of agricultural area, Pop for population density, Trd for trade openness, and Ins as a proxy to catch the level of institutions (or democracy). All right-hand variables are expressed in natural logarithms.

3.3.1 Results and discussion

Results are reported in the following Tables 3.10 and 3.12 where the models with and without the variable of institutions have been implemented. Furthermore, even results with Driskoll and Kraay robust standard errors has been reported (Tables 3.10 and 3.13).[44] The low income group preserves the U-shape relationship encountered in the previous model, but with far less significance. The linear model shows higher significance for the GDP terms, positively associated with deforestation. Agriculture, as expected, has a positive impact on deforestation, even if the significance holds only with the model which includes even institutions as control variable, negatively associated with deforestation. Eventually, trade openness results to be not significant.

Even in the middle income group the EKCd shape tends to fade away by preferring a linear relationship which negatively associates GDP with deforestation: more economic growth, less deforestation. The EKCd holds at 10% level of significance only when the variable of institution is considered. Despite the positive sign,

[44]Tests for the presence of heteroscedasticity, serial correlation, and cross-sectional dependency for these models could be found in Appendix A (Tables A.4 to A.6).

agricultural area results to be not particularly significant with a robust estimation[45] while population density and trade openness does but with negative coefficients. Therefore, a more freely trade and an increase in population density should led to less deforestation. The two sub-groups of lower- and upper-middle economies does not present significant coefficients for GDP in their robust estimations while population density, trade openness, and institutions show a general—even if not always significant—negative impact on deforestation.

Moving to the last group of high income economies, here the U-shape relationship holds with high significance even with the robust estimation while the only additional significant variable is population density, even for this group with a negative coefficient. Albeit unexpected, this negative relationship between population and deforestation rates could be explained by the process of urbanization which characterizes several developing countries (and continues even more in industrialized countries). Individuals, moving from marginal rural areas and in general from agricultural and forestry activities, look for better off-farm employments which reduces their direct impact on deforestation. Conversely, in some other cases, high labor-intensive agro-forestry activities could lead to an increment of population without a necessarily negative impact on forests. Nonetheless, the relationship between deforestation and population still remains debated and this variables is often considered endogenously.

Eventually, with the inclusion of additional control variables, the TPs of the groups are different from those previous identified. For the low income group, the GDP level at what deforestation rates start to rises is equal to US$ 284.29 (US$ 259.82 without the variable of institution). In the middle income group the EKCd's TP settles at US$ 685.39 (US$ 796.32) while for high income economies reforestation rates start to decrease at US$ 1,772.24 (US$ 2,368.47). Even in this case the solutions of the quadratic equation for the low income group are imaginaries meaning that the

[45] Agriculture area results to be significant only in the model without robust standard errors and in particular with the model without institutions. In this specification agriculture is significant only for the whole middle group and for upper-middle countries. Although it seems a little surprising the fact that only the upper-middle group shows a significant result, an explication could be provided. In the low income group countries are mostly in phase I and II of the FDP and in the first one the ratio between forest decrease and agriculture expansion is reasonably around one (this can be a source of endogeneity for this group too). In fact, despite the lack of long-run relationship, the variable of agriculture is positively related to deforestation and significant. In the lower-middle income group countries mostly lies in phases II and III of the FDP where the relationship between agriculture and deforestation in the former phase is no longer equal to one. Eventually, for the upper-middle income group, where countries are mostly in phase III and beyond, agricultural area now compete with management forests. Then, this competition could explain the positive significance of agriculture only for this income group.

Table 3.10 *Enlarged EKCd model with FE*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0269	0.00268***	-0.0352***	-0.00111	0.0115**	-0.00189***	0.0073	0.000382	-0.0313***	0.00752***
	(0.001)	(0.013)	(0.001)	(0.005)	(0.001)	(0.007)	(0.001)	(0.007)	(0.001)	
GDP^2	0.00238		0.00238**		-0.000880**		-0.000446		0.00209***	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
Agr	0.0121***	0.0127***	0.000578	-0.0000499	0.00462**	0.00610***	0.00355	0.00445	0.00236	-0.00128
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Pop	0.00301**	0.00278*	-0.00282**	-0.00287**	-0.00681***	-0.00730***	-0.0160***	-0.0165***	-0.0278***	-0.0235***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Trd	0.000835	0.000485	-0.00155**	-0.00205***	-0.00234***	-0.00190***	-0.00236**	-0.00204**	-0.00181	-0.00171
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ins	-0.00248***	-0.00257***	-0.00163***	-0.00152***	-0.00312***	-0.00310***	-0.00573***	-0.00570***	-0.00141**	-0.00208***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$Constant$	0.102*	0.0121	0.144***	0.0240***	-0.0159	0.0339***	-0.0201	0.00541	0.0958***	-0.0821***
	(0.055)	(0.008)	(0.048)	(0.008)	(0.021)	(0.006)	(0.027)	(0.009)	(0.032)	(0.010)
Observations	762	762	1,177	1,177	2,386	2,386	1,209	1,209	1,160	1,160
AIC	-5427.8	-5427.1	-7904.9	-7900.2	-15698.7	-15694.3	-7924.8	-7925.8	-8339.9	-8307.8
BIC	-5395.4	-5399.2	-7869.5	-7869.8	-15658.2	-15659.7	-7889.1	-7895.2	-8304.5	-8277.4

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

Table 3.11 *Enlarged EKCd model with FE (Driscoll and Kraay robust standard errors)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0269*	0.00268***	-0.0352	-0.00111	0.0115*	-0.00189**	0.0073	0.000382	-0.0313***	0.00752***
	(0.015)	(0.001)	(0.022)	(0.002)	(0.007)	(0.001)	(0.008)	(0.001)	(0.009)	(0.001)
GDP^2	0.00238*		0.00238		-0.000880*		-0.000446		0.00209***	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
Agr	0.0121*	0.0127*	0.000578	-0.0000499	0.00462	0.0061	0.00355	0.00445	0.00236	-0.00128
	(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
Pop	0.00301	0.00278	-0.00282	-0.00287*	-0.00681***	-0.00730***	-0.0160***	-0.0165***	-0.0278***	-0.0235***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)
Trd	0.000835	0.000485	-0.00155	-0.00205*	-0.00234**	-0.0019	-0.00236	-0.00204	-0.00181	-0.00171
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Ins	-0.00248*	-0.00257*	-0.00163*	-0.00152*	-0.00312***	-0.00310***	-0.00573***	-0.00570***	-0.00141	-0.00208
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$Constant$	0.102**	0.0121	0.144	0.024	-0.0159	0.0339***	-0.0201	0.00541	0.0958*	-0.0821***
	(0.050)	(0.012)	(0.087)	(0.018)	(0.028)	(0.010)	(0.036)	(0.015)	(0.049)	(0.014)
Observations	762	762	1,177	1,177	2,386	2,386	1,209	1,209	1,160	1,160

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. The maximum lag order considered for the autocorrelated structure is 3.

Table 3.12 *Enlarged EKCd model with FE (no institutions)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0339*	0.00344***	-0.0350***	-0.000942	0.00962*	-0.00136**	0.00689	0.000876	-0.0350***	0.00651***
	(0.018)	(0.001)	(0.013)	(0.001)	(0.005)	(0.001)	(0.007)	(0.001)	(0.006)	(0.001)
GDP^2	0.00300**		0.00238**		-0.000720**		-0.000387		0.00225***	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
Agr	0.00980**	0.0105***	0.00105	0.000616	0.00580***	0.00687***	0.00749**	0.00819***	0.00158	-0.00294
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Pop	0.000225	-0.00019	-0.00535***	-0.00530***	-0.0102***	-0.0106***	-0.0191***	-0.0196***	-0.0286***	-0.0245***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
Trd	0.000896	0.000453	-0.00117	-0.00165**	-0.00252***	-0.00216***	-0.00429***	-0.00401***	-0.00171	-0.00139
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Constant$	0.110*	-0.00389	0.137***	0.0170**	-0.0195	0.0212***	-0.0264	-0.00422	0.111***	-0.0813***
	(0.056)	(0.008)	(0.047)	(0.008)	(0.021)	(0.006)	(0.027)	(0.009)	(0.031)	(0.009)
Observations	762	762	1,193	1,193	2,475	2,475	1,282	1,282	1,180	1,180
AIC	-5410.1	-5407.8	-8004.9	-8000.1	-16292.9	-16290.6	-8371.7	-8372.9	-8499.4	-8459.2
BIC	-5382.3	-5384.6	-7974.4	-7974.7	-16258.1	-16261.5	-8340.7	-8347.1	-8468.9	-8433.8

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

Table 3.13 *Enlarged EKCd model with FE (no institutions, D-K robust standard errors)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0339**	0.00344***	-0.035	-0.000942	0.00962	-0.00136*	0.00689	0.000876	-0.0350***	0.00651***
	(0.016)	(0.001)	(0.022)	(0.002)	(0.007)	(0.001)	(0.008)	(0.001)	(0.013)	(0.002)
GDP^2	0.00300**		0.00238		-0.00072		-0.000387		0.00225***	
	(0.001)		(0.001)		(0.000)		(0.001)		(0.001)	
Agr	0.0098	0.0105	0.00105	0.000616	0.0058	0.00687*	0.00749	0.00819	0.00158	-0.00294
	(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)	(0.006)
Pop	0.000225	-0.00019	-0.00535***	-0.00530***	-0.0102***	-0.0106***	-0.0191***	-0.0196***	-0.0286***	-0.0245***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
Trd	0.000896	0.000453	-0.00117	-0.00165	-0.00252**	-0.00216*	-0.00429**	-0.00401**	-0.00171	-0.00139
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.110**	-0.00389	0.137	0.017	-0.0195	0.0212**	-0.0264	-0.00422	0.111	-0.0813***
	(0.049)	(0.007)	(0.085)	(0.017)	(0.028)	(0.009)	(0.033)	(0.012)	(0.067)	(0.015)
Observations	762	762	1,193	1,193	2,475	2,475	1,282	1,282	1,180	1,180

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

curve utterly lies in the area where deforestation rates are positive (no FT occurs).[46] Moreover, considering the whole middle income group, deforestation rates now reach the zero level an higher income level equal to US$ 97,733. However, the solution from the model without institution provides a result remarkably different equal to US$ 52,052.07, a value mostly like the GDP per capita of US in 2017 (US$ 53,128 in 2010 constant prices) (WB, 2017).[47] Eventually, for the high-income group the two solutions now range between US$ 73 (US$ 83.93) and US$ 43,477.55 (US$ 66,836.19). Even in this case the solutions between the two models are highly different. However, the variable of institution (which results to be not significant in both models) is mostly stable over time for these countries (long-term democracies). Therefore, especially for this case the model without institutions would be more reliable.

The pattern emerged with this second analysis is slightly more puzzled if compared with the one where only GDP was considered. A U-shape pattern emerges for both low and lower-middle economies. However, for the whole middle group, even if with reduced significance, the classic EKC's shape holds but with an higher GDP per capita level compared to the one previous identified and the FT occurs remarkably high GDP level. The U-shape of reforestation is confirmed with high significance for the high income group but with a lower turning point. As expected,

[46]The same occurs even for the sub-group of lower-middle economies which also shows a U-shape pattern with a TP achieved at a US$ 1,619.7 (US$ 1,556.19 without the variable of institution). The imaginary solutions of the quadratic formula seem to suggest even in this case the not-achievement of the FT but rather a return in deforestation with relatively high income levels. However, results from the robust estimations are not significant for this group of countries.

[47]The other solution of the quadratic formulation for the middle income group is equal to about US$ 4.8 and US$ 12.6, respectively. Even in this case, as expected, a truly low value.

agriculture has a negative impact on forest cover spurring deforestation for low and middle economies while population density has rather an opposite effect. Moreover, a more freer market helps to flatten the EKCd for middle income economies. In the high income group the TP for reforestation occurs at a lower GDP level and even more the FT, with an opposite tendency compared to middle income economies. Therefore, with the presence of control variables the "discrepancy" between the FT for middle and high income economies increases remarkably meaning that it would require more "time"—or rather development—before developing countries could reach a level of zero deforestation.

3.3.2 All income economies

The same estimation for all economies performed in Section 3.2.6 is now presented with the addition of the control variables introduced in the previous Section 3.3.1. Moreover, when deforestation rates for natural forest is chosen ad dependent variable, the additional control variable of planted forest (Pla) is included in the model.[48] Even in this case the analysis has been carried out with and without the variable of institutions (Ins). Results for the linear, quadratic, and cubic formulation are reported in the following Tables 3.14 to 3.17. The cubic specification with its N-shape curve results the preferred one according to AIC and BIC. Concerning the control variables, agriculture area has a positive relationship with deforestation, even if the statistical significance is only at 10% with the robust estimation. For natural forest, a low significance holds only when the variable of institution is not considered in the model. This low significance could be due to the fact that along the three stages of the FDP the relationship between agriculture and natural forest changes and so among the income-clusters. For example, no direct relationship is expected to be observed for the group of high income economies. Therefore, since the relationship between agriculture and forest changes along the development of economies, the average effect could results to be of low significance or even not significant.[49] Moreover, population density, trade openness, and level of institutions are all negatively related to deforestation.[50] As for natural forest, among these variables, only institutions has a significant and negative relationship. Furthermore, it is important to stress out the

[48]Descriptive statistic for this variable is reported in Appendix A (Table A.1).

[49]Results for the income groups, showed in Appendix A, sustain this conclusion since the positive coefficient of agriculture is significant for low and middle economies, but not for the high income group.

[50]Surprisingly, in the high income group both population density and trade openness have a positive and significant coefficient (Appendix A, Tables 3.14 to 3.17).

negative and significant impact of forest plantation over natural forest deforestation, hence a driver to reduce the exploitation of these threatened forests.

The TP corresponding to the peak of the EKCd for total and natural forests are equal to US$ 550 and 542,4, respectively. The second TPs are equal to US$ 12,721 for total forest and to US% 25,336 for natural forests. Conversely, when the variable *Ins* is not included in the model, the first TP is equal to US$ 638 for total forest and to US$ 633 for natural forest while the second TPs to US$ 11,159 and 21,375.4, respectively. Eventually, in this case results for FTs could not be retrieved since the second and the third solution from the cubic formulation are imaginaries for both total and natural forest (with and without institutions as additional control variable). Therefore, despite preserving the expected N-shape, the curve for the two forest categories lies in the area of deforestation. The interpretation, following the first studies for the EKC, should suggest that for high income levels a return in deforestation is expected rather than the achievement of a FT. This results is for sure tricky if compared with the previous model presented in this section where, despite different results from the basic model, still a faint shape of the EKCd could be found. Nonetheless, the fact that for the lower-middle income group results in Tables 3.14 to 3.17 concluded for a U-shape with a relatively high TP—in contrast with he reverse shape for the whole middle group—seems to suggest a possible oscillatory tendency for the middle income group which could explain the results for the model with all countries. Moreover, even the fact that for both lower- and upper-middle economies results are of a U-shape for natural forest (see Tables A.7 to A.10 in Appendix A) could sustain the idea of an oscillatory tendency along the decreasing path of the EKCd.

3.4 Stationarity and cointegration

Panel data techniques are becoming more and more common in economic discipline since they can provide information from both the cross-country and time-series dimensions. However, while these techniques are suitable for microeconomic databases where the number of individuals N overcomes their observation over time T ($N > T$), the increasing amount of macroeconomic database such as that used in this analysis, are leading to the case where N and T are both large ($N = T$) or even where T overtakes the cross-sectional dimension.[51] Hence, in this case panel

[51] The work of Eberhardt and Teal (2011) shows recent advancements in panel data techniques when both N and T dimensions are large.

Table 3.14 *Enlarged EKCd model with FE for total forest (all income economies)*

Def (total forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.000454	-0.000454	-0.0109***	-0.0109***	0.112***	0.112***
	(0.000)	(0.001)	(0.002)	(0.004)	(0.014)	(0.014)
GDP^2			0.000661***	0.000661***	-0.0148***	-0.0148***
			(0.000)	(0.000)	(0.002)	(0.002)
GDP^3					0.000626***	0.000626***
					(0.000)	(0.000)
Agr	0.00315**	0.00315	0.00645***	0.00645*	0.00676***	0.00676*
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)
Pop	-0.00445***	-0.00445***	-0.00499***	-0.00499***	-0.00482***	-0.00482***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Trd	-0.00113**	-0.00113	-0.00104**	-0.00104	-0.00184***	-0.00184**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Ins	-0.00213***	-0.00213**	-0.00224***	-0.00224**	-0.00205***	-0.00205**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
$Constant$	0.0160***	0.016	0.0591***	0.0591***	-0.256***	-0.256***
	(0.004)	(0.010)	(0.011)	(0.018)	(0.036)	(0.037)
Observations	4308	4308	4308	4308	4308	4308
AIC	-29005.1		-29022.3		-29106.9	
BIC	-28966.9		-28977.8		-29056	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

Table 3.15 *Enlarged EKCd model with FE for total forest (all income economies, no institutions)*

Def (total forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.000221	-0.000221	-0.0100***	-0.0100***	0.116***	0.116***
	(0.000)	(0.001)	(0.002)	(0.003)	(0.013)	(0.014)
GDP^2			0.000617***	0.000617***	-0.0152***	-0.0152***
			(0.000)	(0.000)	(0.002)	(0.002)
GDP^3					0.000642***	0.000642***
					(0.000)	(0.000)
Agr	0.00333**	0.00333	0.00628***	0.00628*	0.00684***	0.00684*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Pop	-0.00690***	-0.00690***	-0.00751***	-0.00751***	-0.00715***	-0.00715***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Trd	-0.00122***	-0.00122	-0.00115**	-0.00115	-0.00198***	-0.00198**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
$Constant$	0.00714**	0.00714	0.0471***	0.0471***	-0.276***	-0.276***
	(0.004)	(0.008)	(0.010)	(0.016)	(0.035)	(0.036)
Observations	4417	4417	4417	4417	4417	4417
AIC	-29766.7		-29782.1		-29873.8	
BIC	-29734.7		-29743.7		-29829.1	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

Table 3.16 *Enlarged EKCd model with FE for natural forest (all income economies)*

Def (natural forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.00387***	-0.00387***	0.00051	0.00051	0.129***	0.129**
	(0.001)	(0.001)	(0.007)	(0.008)	(0.040)	(0.050)
GDP^2			-0.000282	-0.000282	-0.0166***	-0.0166**
			(0.000)	(0.001)	(0.005)	(0.006)
GDP^3					0.000673***	0.000673**
					(0.000)	(0.000)
Agr	0.0118***	0.0118	0.0106**	0.0106	0.0118**	0.0118
	(0.004)	(0.008)	(0.005)	(0.007)	(0.005)	(0.007)
Pla	-0.00314***	-0.00314***	-0.00313***	-0.00313***	-0.00317***	-0.00317***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pop	0.00192	0.00192	0.00214	0.00214	0.00221	0.00221
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Trd	0.000968	0.000968	0.000903	0.000903	0.000227	0.000227
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Ins	-0.00311***	-0.00311***	-0.00308***	-0.00308***	-0.00293***	-0.00293***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.0377***	0.0377	0.0204	0.0204	-0.303***	-0.303***
	(0.012)	(0.025)	(0.030)	(0.028)	(0.103)	(0.113)
Observations	4,094	4,094	4,094	4,094	4,094	4,094
AIC	-19630.9		-19629.3		-19638.5	
BIC	-19586.6		-19578.7		-19581.6	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

data analysis necessarily have to deal with common time-series problematics. The main issue to assess is the stationarity of the series under exams in order to avoid possible spurious regressions (Granger and Newbold, 1974) which becomes even more problematic in the case of panel data when both N and T tend to go to infinite (Baltagi, 2013). In the presence of non stationary variables it is not possible to rely on the results obtained by the relationship between two or more variables since they could be independent albeit highly correlated (with an high R^2) only because of their trend. Variables such as GDP per capita (*e.g.* Nelson and Plosser, 1982) are commonly considered non-stationary variable, expressed as $I(1)$ which means that they have to be firs-differentiated one time in order to be stationary and be cleaned up by the stochastic trend which commonly characterize them.[52]

Non-stationary series could be related by a common path or rather be cointegrated, as first suggested by Granger and Weiss (1983) and then in Engle and Granger (1987). Briefly, if two time series Y and X are integrated of order d, it means that to

[52]Non-stationary variables are even called non-mean reverting, meaning that the item of the variable does not have the tendency to revert through time to the mean value.

Table 3.17 *Enlarged EKCd model with FE for natural forest (all income economies, no institutions)*

Def (natural forest)	**Linear**		**Quadratic**		**Cubic**	
		D-K		***D-K***		***D-K***
GDP	-0.00337***	-0.00337**	0.0013	0.0013	0.134***	0.134***
	(0.001)	(0.001)	(0.007)	(0.008)	(0.039)	(0.049)
GDP^2			-0.0003	-0.0003	-0.0171***	-0.0171***
			(0.000)	(0.001)	(0.005)	(0.006)
GDP^3					0.000694***	0.000694***
					(0.000)	(0.000)
Agr	0.0118***	0.0118	0.0106**	0.0106	0.0120***	0.0120*
	(0.004)	(0.007)	(0.005)	(0.006)	(0.005)	(0.007)
Pla	-0.00306***	-0.00306**	-0.00305***	-0.00305**	-0.00311***	-0.00311***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pop	-0.00208	-0.00208	-0.00181	-0.00181	-0.00156	-0.00156
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Trd	0.000777	0.000777	0.00071	0.00071	0.00000155	0.00000155
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
$Constant$	0.0238**	0.0238	0.00549	0.00549	-0.328***	-0.328***
	(0.011)	(0.024)	(0.029)	(0.029)	(0.100)	(0.109)
Observations	4,182	4,182	4,182	4,182	4,182	4,182
AIC	-20126.5		-20125		-20135.4	
BIC	-20088.5		-20080.6		-20084.7	

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

be stationary they have to be differentiated d-times. Even if they are non stationary in levels, they are considered co-integrated if a combination of them is of an order of integration lower than d (the residuals from their co-integrating regression result to be integrated of an order lower than d). Most of the macroeconomic time series, especially those investigated within the EKC literature, usually deal with variable where $d = 1$; therefore, to conclude for the presence of co-integration the residuals of their co-integrating regression should be stationary or rather $I(0)$. If the analysis conclude for the presence of co-integration, then the relationship between Y and X (and other independent variables) is not spurious—they do not drift apart from each other—and it does tell something about the long-run relationship which occur between them.

The models presented so far has been always static, then without considering the dynamic which relates the variables and especially without considering their behavior over time. Therefore, of crucial importance is to test the stationarity of the variable under exams and the possible presence of cointegration among them. Eventually, a more advanced and dynamic model will be performed in Section 3.5 able to deal with both short and long run dynamics.

3.4.1 Unit root tests

The first step is to test the order of integration of the variables under examination: deforestation rates (Def_{it}), GDP per capita (GDP_{it}), and its squared value (GDP^2_{it}). Two unit root tests have been implemented. The first one, considered a first-generation panel unit root test, is the Fisher-type Augmented Dickey-Fuller (ADF) test (Choi, 2001) where the null hypothesis H_0 "all panels contain unit roots" is tested against the alternative H_1 "at least one panel is stationary." The second one, within the second-generation unit root tests, is the Cross-sectional Augmented Dickey-Fuller (CADF) test proposed by Pesaran (2007) which considers the cross-sectional dependence among individuals (previous confirmed in Table 3.5). This test represents an enhancement of the basic unit root tests for heterogeneous panel proposed by Im *et al.* (2003) generalized for unbalanced panels where the null hypothesis H_0 "all panels contain unit roots" is tested against the alternative H_1 "a fraction of the series is stationary." [53]

Tests have been performed with only constant and with constant and trend terms considering one and two lag orders in order to check possible serial correlation in the errors. Results of these unit root tests are reported in Tables 3.18 to 3.21. Concerning GDP variables, they can clearly be considered as $I(1)$ variables since the tests in levels results to be non stationary while in first difference they are all stationary. Results for Def_{it} are quite mixed since tests with one lag seems to identify it as a stationary variable while tests with two lag orders are non stationary even in first difference. Therefore, it is hard to identify clearly the integrating order of this dependent variable. Those results are undoubtedly due to the fact that forest cover data have been reconstructed by means of an interpolation methodology which smoothed the series remarkably. Furthermore, since the ADF test assumes a specific structure for the test equal for each country, it can not be excluded that results of the tests are affected by type I (rejection of a true null hypothesis) or type II error (fail to reject a false null hypothesis). However, forest cover is a stock variable which changes relatively slow over time without abruptly changes from one year to another[54] and stock variables are commonly identified as $I(2)$ (Haldrup, 1994) meaning that they have to be differentiated two times to become stationary. Accordingly, since deforestation rates is just an negative first difference of forest cover

[53]Note that other first- and second-generation panel unit root tests are presented in the literature; however, most of them could be implemented only with balanced panels.

[54]Especially when the variable under exam has been reconstructed by means of an interpolation.

(when expressed in natural logarithms), in levels it should be an $I(1)$ variable.[55] Eventually, we can conclude that both dependent and independent variables are $I(1)$.

Moving to additional control variables, the same tests (ADF and CADF) have been performed for the variable of agricultural area (Agr), population density (Pop), and trade openness (*Trd*). For the subsequent analysis the variable of institution (Ins) has been left out due to its tendency to change slowly over time, especially for upper-middle and high income economies. Furthermore, since dynamic-panel models (as the one implemented in the following Section 3.5) relies on variables both in levels and in first differences, the use of this particular variables would have resulted in a variable at first differences in most of the cases composed by a series of 1 or 0 which could have biased the results. Eventually, Ins was the most unbalanced variable among those considered, another reason to put it aside.[56] Results are reported in Tables 3.22 to 3.25.

Concerning agricultural area, tests clearly conclude for $I(1)$ variables while for population density and trade openness results are more mixed. In the case of population, the conclusion seems to be for an $I(0)$ variable except for high income economies where results are for an $I(1)$ variable. When the lag order is incremented results change and the conclusion is neither for $I(0)$ nor for $I(1)$. However, when implemented as control variable population density commonly resulted as an $I(1)$ variable (*e.g.* Al Mamun *et al.*, 2014; Atasoy, 2017). In the case of international trade the variable appears to be mostly $I(1)$ for low and high income economies while for the middle income group $I(0)$. Nevertheless, performing the same unit root tests for the two sub-groups of lower- and upper-middle countries, results for the former leads to $I(1)$ while for the latter to $I(0)$ variables. Therefore, considering even the alternative hypothesis for the Fisher ADF tests ("at least one panel is stationary"), it is possible to consider even this variable, as well as population density and agricultural area, integrated of order one.

[55] In fact, the first difference of total forest cover is equal to $\Delta For = For_t - For_{t-1}$, a kind of reforestation rate (which assumes negative values when forest cover losses occurs between t and $t-1$), while deforestation rates is $For_{t-1} - For_t$ and equal to $-\Delta For$. Moreover, although the unit root tests here presented may "even" suggest an order of integration for Def_{it} higher than $I(1)$—then higher than $I(2)$ for For_{it}—, the existence of $I(3)$ processes is highly rare in economics (Haldrup, 1994; Majsterek, 2012). Therefore, with some cautions it is possible to assume that For_{it} is $I(2)$ while Def_{it} is $I(1)$ and the lack of strong results for this conclusion could be due to three reasons: the specific structure of the ADF tests, the reconstruction process of forest cover data, and the possible occurrence of type I and II errors.

[56] In fact, within the EKC literature which implements dynamic models, when the T-dimension is elevated, these kind of variables are hardly considered.

Table 3.18 *ADF unit root test (low income economies)*

Constant, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP_{it}^2		ΔGDP_{it}^2	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	437.0244	0	218.7436	0	20.8556	0.9974	386.569	0	20.4375	0.998	378.4816	0
Inverse normal	Z	-12.5816	0	-10.3269	0	3.9319	1	-15.7144	0	4.1587	1	-15.496	0
Inverse logit t	$L*$	-24.5296	0	-12.9872	0	4.1667	1	-23.243	0	4.4618	1	-22.7445	0
Modified inv. Chi^2	Pm	43.1007	0	19.2843	0	-2.307	0.9895	37.5956	0	-2.3527	0.9907	36.7131	0

Constant + Trend, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP_{it}^2		ΔGDP_{it}^2	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	483.3247	0	189.0686	0	69.0234	0.0054	371.2762	0	64.7616	0.0136	370.9661	0
Inverse normal	Z	-15.3906	0	-9.182	0	0.0598	0.5238	-14.8567	0	0.4064	0.6578	-14.8864	0
Inverse logit t	$L*$	-28.7346	0	-11.1619	0	-0.6949	0.2443	-22.2797	0	-0.2055	0.4188	-22.2622	0
Modified inv. Chi^2	Pm	48.1525	0	16.0465	0	2.9485	0.0016	35.927	0	2.4835	0.0065	35.8931	0

Constant, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP_{it}^2		ΔGDP_{it}^2	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	94.4205	0	95.481	0	17.5545	0.9997	225.9954	0	16.9434	0.9998	220.7019	0
Inverse normal	Z	-0.8446	0.1992	-4.6672	0	4.0419	1	-10.8505	0	4.2511	1	-10.6053	0
Inverse logit t	$L*$	-1.0609	0.1455	-4.9224	0	4.3826	1	-13.3834	0	4.6343	1	-13.0356	0
Modified inv. Chi^2	Pm	5.7195	0	5.8353	0	-2.6672	0.9962	20.0755	0	-2.7339	0.9969	19.498	0

Constant + Trend, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP_{it}^2		ΔGDP_{it}^2	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	84.5152	0.0001	66.2105	0.01	69.4428	0.0049	190.8146	0	62.5711	0.0213	189.5474	0
Inverse normal	Z	-1.7763	0.0378	-2.7004	0.0035	0.1589	0.5631	-9.0972	0	0.6177	0.7316	-9.045	0
Inverse logit t	$L*$	-2.1089	0.0187	-2.812	0.0029	-0.4399	0.3304	-10.8907	0	0.2386	0.5941	-10.8223	0
Modified inv. Chi^2	Pm	4.6388	0	2.6416	0.0041	2.9943	0.0014	16.237	0	2.2445	0.0124	16.0987	0

Notes: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.19 *ADF unit root test (middle income economies)*

Constant, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	728.8474	0	733.6191	0	114.6417	0.8292	930.3345	0	101.8944	0.9675	901.5941	0
Inverse normal	Z	-16.823	0	-18.3212	0	4.6177	1	-22.7798	0	5.0463	1	-22.2933	0
Inverse logit t	$L*$	-23.2597	0	-24.2	0	4.1389	1	-31.5773	0	4.6416	1	-30.5726	0
Modified inv. Chi^2	Pm	37.1389	0	37.4349	0	-0.9525	0.8296	49.6346	0	-1.743	0.9593	47.8522	0

Constant + Trend, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	733.6191	0	609.3662	0	169.9313	0.0107	838.7242	0	170.6796	0.0097	807.9554	0
Inverse normal	Z	-18.3212	0	-15.9546	0	1.8803	0.97	-20.1841	0	2.0018	0.9773	-19.8847	0
Inverse logit t	$L*$	-24.2	0	-19.9748	0	0.4628	0.6781	-28.055	0	0.5274	0.7009	-26.9772	0
Modified inv. Chi^2	Pm	37.4349	0	29.729	0	2.4764	0.0066	43.9532	0	2.5228	0.0058	42.045	0

Constant, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	143.2331	0.2017	327.5957	0	77.1715	0.9999	542.4726	0	69.3678	1	515.4451	0
Inverse normal	Z	-0.3139	0.3768	-8.6935	0	5.0223	1	-15.807	0	5.6985	1	-15.2157	0
Inverse logit t	$L*$	-0.3555	0.3612	-9.6939	0	5.2144	1	-18.1075	0	5.9155	1	-17.1228	0
Modified inv. Chi^2	Pm	0.8207	0.2059	12.2544	0	-3.2763	0.9995	25.5805	0	-3.7602	0.9999	23.9043	0

Constant + Trend, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	118.6209	0.7536	228.7364	0	101.9797	0.967	457.1046	0	99.1571	0.9797	443.2557	0
Inverse normal	Z	1.7555	0.9604	-4.943	0	3.0088	0.9987	-12.5107	0	3.1138	0.9991	-12.2102	0
Inverse logit t	$L*$	1.8781	0.9694	-5.509	0	3.089	0.9989	-14.3977	0	3.1846	0.9992	-13.8607	0
Modified inv. Chi^2	Pm	-0.7057	0.7598	6.1234	0	-1.7377	0.9589	20.2862	0	-1.9128	0.9721	19.4273	0

Notes: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.20 *ADF unit root test (high income economies)*

Constant, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	437.0244	0	218.7436	0	20.8556	0.9974	386.569	0	20.4375	0.998	378.4816	0
Inverse normal	Z	-12.5816	0	-10.3269	0	3.9319	1	-15.7144	0	4.1587	1	-15.496	0
Inverse logit t	$L*$	-24.5296	0	-12.9872	0	4.1667	1	-23.243	0	4.4618	1	-22.7445	0
Modified inv. Chi^2	Pm	43.1007	0	19.2843	0	-2.307	0.9895	37.5956	0	-2.3527	0.9907	36.7131	0

Constant + Trend, 1 Lag		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	483.3247	0	189.0686	0	69.0234	0.0054	371.2762	0	64.7616	0.0136	370.9661	0
Inverse normal	Z	-15.3906	0	-9.182	0	0.0598	0.5238	-14.8567	0	0.4064	0.6578	-14.8864	0
Inverse logit t	$L*$	-28.7346	0	-11.1619	0	-0.6949	0.2443	-22.2797	0	-0.2055	0.4188	-22.2622	0
Modified inv. Chi^2	Pm	48.1525	0	16.0465	0	2.9485	0.0016	35.927	0	2.4835	0.0065	35.8931	0

Constant, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	94.4205	0	95.481	0	17.5545	0.9997	225.9954	0	16.9434	0.9998	220.7019	0
Inverse normal	Z	-0.8446	0.1992	-4.6672	0	4.0419	1	-10.8505	0	4.2511	1	-10.6053	0
Inverse logit t	$L*$	-1.0609	0.1455	-4.9224	0	4.3826	1	-13.3834	0	4.6343	1	-13.0356	0
Modified inv. Chi^2	Pm	5.7195	0	5.8353	0	-2.6672	0.9962	20.0755	0	-2.7339	0.9969	19.498	0

Constant + Trend, 2 Lags		Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	84.5152	0.0001	66.2105	0.01	69.4428	0.0049	190.8146	0	62.5711	0.0213	189.5474	0
Inverse normal	Z	-1.7763	0.0378	-2.7004	0.0035	0.1589	0.5631	-9.0972	0	0.6177	0.7316	-9.045	0
Inverse logit t	$L*$	-2.1089	0.0187	-2.812	0.0029	-0.4399	0.3304	-10.8907	0	0.2386	0.5941	-10.8223	0
Modified inv. Chi^2	Pm	4.6388	0	2.6416	0.0041	2.9943	0.0014	16.237	0	2.2445	0.0124	16.0987	0

Notes: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.21 *CADF unit root test*

Low Income Economies	Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
	Z t-bar	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	***Z t-bar***	**p-value**
Constant, 1 Lag	-7.717	0	-4.296	0	3.295	1	-14.272	0	3.629	1	-14.208	0
Constant + Trend, 1 Lag	-8.801	0	-3.645	0	-1.493	0.068	-13.023	0	-1.283	0.1	-13.064	0
Constant, 2 Lags	-0.675	0.25	-0.198	0.422	4.929	1	-9.438	0	5.158	1	-9.337	0
Constant + Trend, 2 Lags	0.653	0.743	0.974	0.835	0.306	0.62	-8.482	0	0.61	0.729	-8.401	0

Middle Income Economies	Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
	Z t-bar	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	***Z t-bar***	**p-value**
Constant, 1 Lag	-18.378	0	-11.739	0	-0.642	0.26	-18.537	0	-0.235	0.407	-18.082	0
Constant + Trend, 1 Lag	-15.589	0	-10.356	0	-0.536	0.296	-16.666	0	-0.337	0.368	-16.517	0
Constant, 2 Lags	-0.474	0.318	-4.202	0	-0.09	0.464	-13.186	0	0.375	0.646	-12.594	0
Constant + Trend, 2 Lags	3.738	1	-2.177	0.015	0.647	0.741	-10.862	0	0.905	0.817	-10.566	0

High Income Economies	Def_{it}		ΔDef_{it}		GDP_{it}		ΔGDP_{it}		GDP^2_{it}		ΔGDP^2_{it}	
	Z t-bar	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	**Z t-bar**	**p-value**	***Z t-bar***	**p-value**	***Z t-bar***	**p-value**
Constant, 1 Lag	-10.877	0	-11.368	0	2.711	0.997	-10.875	0	2.875	0.998	-10.805	0
Constant + Trend, 1 Lag	-11.903	0	-9.816	0	1.891	0.971	-9.442	0	1.822	0.966	-9.151	0
Constant, 2 Lags	0.48	0.684	-5.172	0	3.333	1	-7.837	0	3.398	1	-7.721	0
Constant + Trend, 2 Lags	0.969	0.834	-2.89	0.002	3.324	1	-6.18	0	3.336	1	-5.85	0

Notes: Cross-sectionally ADF test. H_0 = all panels contain unit roots; H_1 = a fraction of the series is stationary.

Table 3.22 *ADF unit root test for additional variables (low income economies)*

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	32.3935	0.8569	345.4485	0	34.7281	0.7795	487.7709	0	77.6624	0.0007	578.1146	0
Inverse normal	Z	4.1796	1	-14.6499	0	3.5728	0.9998	-16.3377	0	-3.2889	0.0005	-20.8653	0
Inverse logit t	$L*$	4.0509	1	-20.8287	0	3.647	0.9998	-29.0707	0	-3.5781	0.0003	-35.794	0
Modified inv. Chi^2	Pm	-1.0482	0.8527	33.1089	0	-0.7934	0.7862	48.6376	0	3.8911	0	58.4949	0

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	36.5939	0.7066	285.251	0	330.5528	0	552.415	0	81.9421	0.0002	477.1504	0
Inverse normal	Z	1.6428	0.9498	-12.4921	0	-12.4963	0	-18.3255	0	-3.7063	0.0001	-18.1694	0
Inverse logit t	$L*$	1.3482	0.9098	-17.0836	0	-19.4647	0	-33.0726	0	-3.9665	0.0001	-29.3942	0
Modified inv. Chi^2	Pm	-0.5899	0.7224	26.5409	0	31.4837	0	55.6908	0	4.358	0	47.4788	0

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	25.2808	0.9807	250.3265	0	12.5498	1	71.4042	0.0031	69.1505	0.0052	357.2475	0
Inverse normal	Z	4.2856	1	-11.2632	0	6.9643	1	-3.3023	0.0005	-2.5656	0.0051	-15.1843	0
Inverse logit t	$L*$	4.4157	1	-14.835	0	7.7485	1	-3.1989	0.0009	-2.7937	0.0031	-22.0117	0
Modified inv. Chi^2	Pm	-1.8242	0.9659	22.7303	0	-3.2133	0.9993	3.2083	0.0007	2.9624	0.0015	35.4694	0

Trend, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	28.5844	0.9432	210.9697	0	30.9431	0.8958	49.9859	0.1859	57.1355	0.0597	284.7776	0
Inverse normal	Z	1.6226	0.9477	-9.172	0	1.9082	0.9718	-0.535	0.2963	-2.1965	0.014	-12.4876	0
Inverse logit t	$L*$	1.4506	0.9251	-12.04	0	1.9327	0.9721	-0.3196	0.375	-2.1677	0.0162	-17.1016	0
Modified inv. Chi^2	Pm	-1.4638	0.9284	18.4361	0	-1.2064	0.8862	0.8713	0.1918	1.6514	0.0493	27.367	0

Note: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.23 *ADF unit root test for additional variables (middle income economies)*

Constant, 1 Lag		Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	171.7052	0.0084	932.6441	0	606.7468	0	632.9542	0	247.5105	0	1619.7963	0
Inverse normal	Z	1.2427	0.893	-23.1474	0	-9.4922	0	-14.244	0	-4.1572	0	-34.4622	0
Inverse logit t	$L*$	0.9368	0.8252	-31.6211	0	-17.0701	0	-20.3732	0	-5.2557	0	-55.4406	0
Modified inv. Chi^2	Pm	2.5864	0.0048	49.7779	0	29.5666	0	31.1919	0	7.2877	0	92.3932	0

Constant, 1 Lag		Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	103.3521	0.959	817.91	0	817.2314	0	1212.5595	0	230.4483	0	1361.9763	0
Inverse normal	Z	4.3309	1	-20.6548	0	-13.2377	0	-26.0434	0	-3.7769	0.0001	-30.6623	0
Inverse logit t	$L*$	3.952	1	-27.277	0	-23.872	0	-40.7111	0	-4.5196	0	-46.5718	0
Modified inv. Chi^2	Pm	-1.6526	0.9508	42.6624	0	42.6203	0	67.1375	0	6.2295	0	76.4039	0

Constant, 1 Lag		Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	133.9697	0.3878	546.135	0	536.0204	0	155.5686	0.0626	256.994	0	976.1601	0
Inverse normal	Z	1.3423	0.9103	-15.2189	0	-10.6652	0	2.8615	0.9979	-3.4537	0.0003	-24.6004	0
Inverse logit t	$L*$	1.3724	0.9146	-17.9314	0	-14.8886	0	2.2811	0.9884	-5.0529	0	-33.2704	0
Modified inv. Chi^2	Pm	0.2462	0.4028	25.8076	0	25.1803	0	1.5857	0.0564	7.8758	0	52.4766	0

Constant, 1 Lag		Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
		Statistic	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Inverse Chi^2	P	69.5693	1	453.7847	0	81.8197	0.9997	170.8288	0.0095	266.638	0	751.7081	0
Inverse normal	Z	5.0463	1	-12.506	0	6.4945	1	0.6556	0.7439	-2.0779	0.0189	-20.1989	0
Inverse logit t	$L*$	5.0296	1	-14.3855	0	6.6104	1	-0.324	0.3731	-4.6982	0	-25.4099	0
Modified inv. Chi^2	Pm	-3.7478	0.9999	20.0803	0	-2.988	0.9986	2.5321	0.0057	8.4739	0	38.5567	0

Note: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.24 *ADF unit root test for additional variables (high income economies)*

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	46.1814	0.8223	481.813	0	91.4602	0.0019	188.3588	0	48.8814	0.7388	718.3766	0
Inverse normal	Z	2.9867	0.9986	-17.4504	0	-0.3759	0.3535	-7.5819	0	0.75	0.7734	-23.1634	0
Inverse logit t	$L*$	3.3192	0.9994	-25.0557	0	-0.6905	0.2455	-9.0676	0	0.532	0.7022	-37.5485	0
Modified inv. Chi^2	Pm	-0.9278	0.8232	40.2355	0	3.3507	0.0004	12.5067	0	-0.6726	0.7494	62.5887	0

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	66.1577	0.1662	429.1688	0	91.3855	0.002	226.4391	0	122.1241	0	585.2398	0
Inverse normal	Z	0.3914	0.6523	-15.9217	0	-1.079	0.1403	-8.7864	0	-5.0869	0	-20.2936	0
Inverse logit t	$L*$	0.3493	0.6363	-22.1996	0	-1.1614	0.1237	-11.1312	0	-5.331	0	-30.5699	0
Modified inv. Chi^2	Pm	0.9598	0.1686	35.2611	0	3.3436	0.0004	16.105	0	6.2481	0	50.0085	0

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	50.8059	0.6712	321.3166	0	103.4451	0.0001	93.7626	0.0012	44.3456	0.8696	443.5517	0
Inverse normal	Z	3.5457	0.9998	-13.1324	0	-0.3714	0.3552	-2.9975	0.0014	1.5729	0.9421	-17.3773	0
Inverse logit t	$L*$	3.4219	0.9996	-16.5387	0	-1.2042	0.1153	-3.1542	0.001	1.3975	0.9178	-23.1671	0
Modified inv. Chi^2	Pm	-0.4908	0.6882	25.0701	0	4.4831	0	3.5682	0.0002	-1.1012	0.8646	36.6202	0

Constant, 1 Lag		Agr_{it} Statistic	Agr_{it} p-value	ΔAgr_{it} Statistic	ΔAgr_{it} p-value	Pop_{it} Statistic	Pop_{it} p-value	ΔPop_{it} Statistic	ΔPop_{it} p-value	Trd_{it} Statistic	Trd_{it} p-value	ΔTrd_{it} Statistic	ΔTrd_{it} p-value
Inverse Chi^2	P	93.9819	0.0011	256.3586	0	36.6825	0.9786	69.146	0.1115	85.0138	0.0075	343.1635	0
Inverse normal	Z	-0.3766	0.3532	-10.7426	0	2.7844	0.9973	-1.4414	0.0747	-2.826	0.0024	-14.5763	0
Inverse logit t	$L*$	-1.2056	0.115	-12.836	0	2.9063	0.9979	-1.444	0.0754	-2.8645	0.0024	-17.8902	0
Modified inv. Chi^2	Pm	3.5889	0.0002	18.9321	0	-1.8253	0.966	1.2422	0.1071	2.7415	0.0031	27.1344	0

Note: Fisher-type ADF test. H_0 = all panels contain unit roots; H_1 = at least one panel is stationary.

Table 3.25 *CADF unit root test for additional variables*

Low Income Economies	Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}[1]		ΔTrd_{it}[1]	
	Z *t-bar*	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z *t-bar***	**p-value**
Constant, 1 Lag	-2.7	0.003	-11.694	0	-14.735	0	-14.121	0	-2.926	0.002	-15.956	0
Constant + Trend, 1 Lag	-0.835	0.202	-9.816	0	-14.972	0	-13.372	0	-1.114	0.133	-14.494	0
Constant, 2 Lags	-2.847	0.002	-9.096	0	1.128	0.87	-0.167	0.434	-2.014	0.022	-11.504	0
Constant + Trend, 2 Lags	-1.445	0.074	-7.198	0	2.153	0.984	4.039	1	-0.157	0.437	-9.814	0

Middle Income Economies	Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
	Z *t-bar*	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z *t-bar***	**p-value**
Constant, 1 Lag	1.631	0.949	-18.012	0	-9.307	0	-18.463	0	-4.581	0	-26.128	0
Constant + Trend, 1 Lag	5.451	1	-15.736	0	-8.463	0	-18.365	0	-0.888	0.187	-23.952	0
Constant, 2 Lags	1.79	0.963	-10.844	0	4.384	1	0.801	0.789	-3.401	0	-17.321	0
Constant + Trend, 2 Lags	5.528	1	-7.579	0	12.929	1	4.229	1	0.401	0.656	-13.965	0

High Income Economies	Agr_{it}		ΔAgr_{it}		Pop_{it}		ΔPop_{it}		Trd_{it}		ΔTrd_{it}	
	Z *t-bar*	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z t-bar**	**p-value**	**Z *t-bar***	**p-value**	**Z *t-bar***	**p-value**
Constant, 1 Lag	-0.49	0.312	-13.923	0	1.304	0.904	-7.625	0	-4.755	0	-15.664	0
Constant + Trend, 1 Lag	-1.128	0.13	-12.894	0	-3.937	0	-6.936	0	-3.665	0	-13.663	0
Constant, 2 Lags	-0.116	0.454	-9.266	0	5.744	1	-1.686	0.046	-3.531	0	-10.412	0
Constant + Trend, 2 Lags	-0.69	0.245	-7.472	0	3.122	0.999	-0.637	0.262	-2.116	0.017	-8.264	0

Notes: Cross-sectionally ADF test. H_0 = all panels contain unit roots; H_1 = a fraction of the series is stationary.
[1] This results has been obtained by removing from the low income group Eritrea and Ethiopia due to short time-span.

3.4.2 Cointegration tests

After performing the unit root tests for the variables of the analysis and concluding that all the variables under investigation are generally $I(1)$, the next step is to test the possible presence of cointegration among them. Therefore, three specific cointegration tests for panel data have been performed: Kao (1999), Pedroni (1999), and Westerlund (2005). All these tests have a common null hypothesis H_0 of "no cointegration" and alternative H_1 "all panels are co-integrated".[57] The Kao test presents five different statistical tests, the Pedroni test three, while the Westerlund test performs only one statistical test. Results are reported first for the model with only GDP and GDP^2 as independent variables (Table 3.26) and then with the additional variables Agr, Pop, and Trd (Table 3.27). The Kao test has been performed only with the inclusion of the constant term while the Pedroni and the Westerlund tests have been performed even with the inclusion of the deterministic trend. Both basic and enlarged models tend to conclude for the presence of cointegration (even if not all tests reject the null hypothesis), especially the Westerlund tests.

3.5 A Pooled Mean Group estimation

Once verified that all variables are generally non stationary, then $I(1)$, but cointegrated, it is possible to perform another analysis suitable for an heterogeneous panel such as the one under investigation. In this section will be implemented the so-called *Pooled Mean Group* (PMG) estimation proposed by Pesaran *et al.* (1999) for dynamic heterogeneous panels. This model is particularly suitable for time-series panels characterized by heteroscedasticity and non stationarity of the series. The PMG employs an ARDL model for each individuals of the panel by imposing an heterogeneous short-run dynamics among the individuals[58] but a common long-run equilibrium.[59] In other words, each country in the short-run follows a specific pattern while in the long-run each of them adjust to the same tendency. The possible existence of the EKCd is expected to be observed only in the long-run equilibrium

[57]The Westerlund test can be performed even with a different alternative hypothesis of "some panels are co-integrated", but for the purposes of the analysis this test has not been selected.

[58]Or rather in the short-run the model allows the intercepts, coefficients, and error variances to differ among individuals.

[59]Since the PMG is based on a ARDL, it allows to control even for the presence of serial correlation in the model (confirmed in Tables A.5 and 3.4).

Table 3.26 *Cointegration tests (basic model)*

Kao		*Low Income*		*Middle Income*		*High Income*	
Constant		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Dickey-Fuller	t	2.0252	0.0214	-0.4842	0.3141	-3.6538	0.0001
Dickey-Fuller	t	2.2983	0.0108	-0.8869	0.1876	-4.4230	0.0000
Augmented Dickey-Fuller	t	-7.7136	0.0000	-13.8819	0	-15.5465	0.0000
Unadjusted modified Dickey-Fuller	t	3.6545	0.0001	2.7094	0.0034	0.4629	0.3217
Unadjusted Dickey-Fuller	t	4.8237	0.0000	1.5362	0.0622	-3.1256	0.0009

Pedroni		*Low Income*		*Middle Income*		*High Income*	
Constant		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Phillips-Perron	t	0.3519	0.3625	0.3519	0.3625	-0.0222	0.4911
Phillips-Perron	t	1.3656	0.086	1.3656	0.086	2.5152	0.0059
Augmented Dickey-Fuller	t	-5.9199	0.0000	-5.9199	0	2.0804	0.0187
Constant + Trend		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Phillips-Perron	t	0.5408	0.2943	0.5408	0.2943	1.7649	0.0388
Phillips-Perron	t	2.7788	0.0027	2.7788	0.0027	4.6035	0.0000
Augmented Dickey-Fuller	t	0.9544	0.1699	0.9544	0.1699	4.2045	0.0000

Westerlund	*Low Income*		*Middle Income*		*High Income*	
Constant	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Variance Ratio	-2.3212	0.0101	-2.3444	0.0095	-3.2148	0.0007
Constant + Trend	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Variance Ratio	-3.4226	0.0003	-3.6491	0.0001	-1.8432	0.0326

Notes: The three tests are the following: Kao, Pedroni, and Westerlund. H_0 = no cointegration; H_1 = all panels are cointegrated.

for what the ARDL produces consistent and efficient estimates.[60] However, the PMG estimation is not able to account for the presence of cross-sectional dependency among individuals. Nonetheless, by following Chudik and Pesaran (2015) and Al Mamun *et al.* (2018), the ARDL on which the PMG is built could be enhanced with the inclusion of cross-sectional means in the short-run estimation trying to control for cross-correlation among countries. The result is a cross-sectionally augmented ARDL model (CS-ARDL).

3.5.1 The PMG estimator

This estimator for heterogeneous panel data has been largely applied within EKC studies on pollution since it first development by Pesaran *et al.* (1999). Among

[60] Alternatively to the PMG, on one side there is the dynamic FE, where both short- and long-run dynamics are constrained to be equal among individuals, on the other the Mean Group (MG) estimation where both short- and long-run dynamic are heterogeneous and the coefficients of the long-run equation are obtained by their mean among individuals.

Table 3.27 *Cointegration tests (enlarged model)*

Kao		*Low Income*		*Middle Income*		*High Income*	
Constant		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Dickey-Fuller	*t*	2.6605	0.0039	-0.8926	0.186	-4.1286	0.0000
Dickey-Fuller	*t*	3.0971	0.0010	-1.0198	0.1539	-4.7819	0.0000
Augmented Dickey-Fuller	*t*	-7.4006	0.0000	-16.4377	0	-15.5799	0.0000
Unadjusted modified Dickey-Fuller	*t*	3.7382	0.0001	3.434	0.0003	0.0628	0.4750
Unadjusted Dickey-Fuller	*t*	4.9999	0.0000	2.2365	0.0127	-3.5818	0.0002

Pedroni		*Low Income*		*Middle Income*		*High Income*	
Constant		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Phillips-Perron	*t*	0.3519	0.3625	2.6693	0.0038	-0.0222	0.4911
Phillips-Perron	*t*	1.3656	0.086	6.7906	0	2.5152	0.0059
Augmented Dickey-Fuller	*t*	-5.9199	0.0000	9.6602	0	2.0804	0.0187
Constant + Trend		**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Modified Phillips-Perron	*t*	0.5408	0.2943	4.0969	0	1.7649	0.0388
Phillips-Perron	*t*	2.7788	0.0027	8.3252	0	4.6035	0.0000
Augmented Dickey-Fuller	*t*	0.9544	0.1699	9.6835	0	4.2045	0.0000

Westerlund	*Low Income*		*Middle Income*		*High Income*	
Constant	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Variance Ratio	-2.3212	0.0101	-2.6984	0.0035	-3.2148	0.0007
Constant + Trend	**Statistic**	**p-value**	**Statistic**	**p-value**	**Statistic**	**p-value**
Variance Ratio	-3.4226	0.0003	-2.8325	0.0023	-1.8432	0.0326

Notes: The three tests are the following: Kao, Pedroni, and Westerlund. H_0 = no cointegration; H_1 = all panels are cointegrated.

the primer studies which implemented the PMG, Perman and Stern (2003) cast doubts on the existence of the EKC for sulfur emissions while Martínez-Zarzoso and Bengochea-Morancho (2004) concluded for an N-shape curve between CO_2 and GDP. Among recent works that implemented this estimator, Atasoy (2017) investigated the EKC for CO_2 within US States, Al Mamun *et al.* (2014) conducted a cross-country analysis for development levels while Mazzanti and Musolesi (2013) analyzed North- and South-European groups countries. These results tend to confirm the presence of an EKC. However, the augmented version of the PMG is still scanty in this literature. Regarding studies on the EKCd, dynamic estimator for large panels such as the PMG have never been applied, therefore, this application represents a primer within this literature.

The PMG estimation is based on an ARDL (p, q_1, ..., q_k) model for each individual which can be written in the following dynamic panel specification (eq. 3.5) developed for the specific EKCd:

$$Def_{it} = \sum_{j=1}^{p} \lambda_{it} Def_{i,t-j} + \sum_{j=1}^{q} \delta'_{it} X_{i,t-j} + \alpha_i + \epsilon_{it} \tag{3.5}$$

where i = 1, 2, ..., N is the number of individuals and t = 1, 2, ..., T the observations repeated over time. Furthermore, Def_{it} is the dependent variable of total deforestation rates and λ_{it} is a scalar coefficients of the lagged values of the dependent variable while X_{it} is a general k x 1 vector of independent variables which regroup GDP_{it}, GDP^2_{it}, and possible additional explanatory variables with the corresponding δ_{it} which is the k x 1 vector of coefficients. Eventually, α_i is the specific individual effect while ϵ_{it} is the idiosyncratic error of the model.

To perform the ARDL model is required that all variables have an order of integration between $I(0)$ and $I(1)$ as well as their cointegration. Therefore, since the presence of cointegration is confirmed (Tables 3.26 and 3.27) and the unit root tests (Tables 3.18 to 3.25) showed how the variables range between $I(0)$ and $I(1)$, the PMG could be applied to investigate the panel in exam. Characteristic of cointegrated variables is their response to any deviation from the long-run equilibrium; therefore, following the primer proposition of Engle and Granger (1987), this feature implies an error-correction model where the short-run dynamic of the model is influenced by the deviation from the equilibrium (represented by the cointegrating equation). Hence, equation 3.5 can be re-parametrized into the following error-correction equation 3.6:

$$\begin{aligned} \Delta Def_{it} = \phi_i (Def_{i,t-1} - \theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{it} \Delta Def_{i,t-j} + \sum_{j=1}^{q-1} \\ + \delta'^*_{it} X_{i,t-j} + \nu_i \overline{Def_t} + v_i \overline{X_t} + \alpha_i + \epsilon_{it} \end{aligned} \tag{3.6}$$

where $\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{it})$, $\theta_i = \sum_{j=0}^{q} / (1 - \sum_k \lambda_{ik})$, $\lambda^*_{it} = -\sum_{m=j+1}^{p} \lambda_{im}$ with j = 1, 2, ..., p - 1, and $\delta^*_{it} = -\sum_{m=j+1}^{q} \delta_{im}$ with j = 1, 2, ..., q - 1. Furthermore, the cross-sectional means of Def_{it} and X_{it} has been added to the re-parametrized model where ν_i and v_i are they relatives k x 1 coefficients vectors. With these additional parameters it is possible to refer to this model as a CS-ARDL. The parameter ϕ_i represents the error-correction term or rather the speed of adjustment to the long-run equilibrium (represented by the cointegrating equation inside the parenthesis where the vector θ'_i contains the long-run relationship between Def_{it} and the other independent variables) and it has to be negative and significant. The coefficient of ϕ_i should range between -1, immediate adjustment to the long-run equilibrium for a disequilibrium occurred in time t_1, and 0, no evidence of an adjustment.[61] Eventually, since the PMG assumes heterogeneity in the short-run but constrain the long run coefficients, equation 3.6 is nonlinear in the parameters. Therefore, Pesaran *et al.* (1999) developed a pooled maximum likelihood estimation to estimate the parameters.[62]

3.5.2 Results and discussion

The PMG estimator has been performed for the three income groups of low, middle, and high income economies, first with the basic specification with only GDP and GDP^2. Results are reported in Table 3.28. The lag order of the ARDL has been selected according to AIC and BIC and results are reported in the following Table 3.28.[63] The attention is focused on the results of the long-run equilibrium where could be retrieved the three shapes identified in the static model: U-shape for low and high income and reverse U-shape for middle income economies. Therefore, the same functional form continues to hold even though the TPs are quite different, especially for the middle income group. For the low income group the TP is equal to US$ 424.11, for middle incomes US$ 7,044.48, while for high income is equal to US$ 18,864. Therefore, the TP for the middle income group now could be achieved only at a relative high income level, far more different from the US$ 200 of the first model (eq. 3.2). Moreover, by looking at the ECTs, all of them result significant and negative, as expected, even if the level of significance for the low income group is only at 5%. Furthermore, the speed of adjustment is particularly low for this group, equal only to 6% while for middle and high is around 12%. The low speed of adjustment

[61] Sometimes even values higher than 1 (but less than 2) could be retrieved in literature (*e.g.* Loayza and Ranciere, 2006) meaning that the equilibrium is achieved through an oscillatory convergence. However, similar results are rather sporadic and debated. Conversely, positive values of this coefficient would suggest a divergence to a possible long-run equilibrium rather than a convergence.

[62] It must be stressed out some differences between the model implemented here and the one proposed by Chudik and Pesaran (2015) and applied for example in Chudik *et al.* (2013) or the one performed by Al Mamun *et al.* (2018). In the former, the MG rather than the PMG estimator has been performed and the cross-sectional means—included only in the short-run dynamic—has been lagged up to the third order to catch the dynamic pervasiveness of the cross-correlation among individuals. In the latter, cross-sectional means have been included both in short- and long-run dynamics (even only in one dynamic per time). However, compared with the work of Chudik *et al.* (2013) cross-sectional mean have been calculated in a slightly different way and without lagged values of them. For the purposes of this study the proposition of Chudik and Pesaran (2015) has been followed but without lagged values of the cross-sectional means due to the limitations of the unbalanced panel in exam and the relative short-time coverage of some countries.

[63] Due to short time-coverage, in the low income group Eritrea and Ethiopia have been removed from the dataset.

is justified by the fact that, despite the existence (or not) of the EKCd, it would be reasonable to expect a low adjustment in a long-run relationship between GDP and forests use.[64] Eventually, in this case it is not possible to determine punctual values for the FT since the constant is the one of the short-run equation (obtained as a mean of the constants of each state) while the interest relies on the long-run equilibrium. In fact, the solutions of the quadratic formula for the three income groups are imaginaries. Therefore, despite the impossibility to determine a proper solution, by considering the TP of the middle income group, for sure the achievement of the FT would occur at high income levels unless the slope of the decreasing side of the EKCd is particularly—but unlikely—steep.

In the second model agricultural area (Agr), population density (Pop), and trade openness (Trd) have been added as additional variables. Results are reported in Table 3.29.[65]. Considering the relative-short time coverage of those additional variables for some countries—differently from the model with only GDP and GDP^2—, for each individual has been performed an ARDL with one lag for each variables. Results show how the functional form hold for all three income clusters even if the TPs change if compared with the previous model: US$ 244,60 for low, US$ 3,789.54 for middle, and US$ 766,814.34 for high income economies. It can be observed how the TPs for low and middle income economies has decreased while in the high income group it now reaches an extremely high level meaning how the process of reforestation continues without reaching a reasonable TP or a re-switch point. Furthermore, agricultural area has a positive impact on deforestation only for the low income group, where countries are mostly in phases I and II of the FDP, while it loses significance (but preserves the positive sign) in the middle income group. Conversely from the static model (eq. 3.4), now population has a positive effect on deforestation for both low and middle income, while it has a negative coefficient only for high income economies. This result is more in line with the general perspective that population spurs deforestation, especially in low income economies (higher coefficient). However, moving to higher income economies the coefficient of population density decrease until the sign becomes negative. Therefore, higher level of development generates better off-farm jobs which decrease the impact of population on forest depletion until more population leads even to a decrease in deforestation

[64]Even the reconstruction of the data for sure would influence this relationship and the low speed of adjustment. In fact, while GDP (and the other variables used) is punctually reported annually, in the case of forests the availability of data allows only to have interpolated values over different time windows.

[65]Due to short time-coverage of some additional variables, Myanmar and Serbia have been removed from the dataset.

Table 3.28 *EKCd model with PMG estimator (CS-ARDL)*

	Low Income	*Middle Income*	*High Income*
Long Run Equation			
GDP	-0.0386***	0.0128***	-0.0827***
	(0.008)	(0.003)	(0.003)
GDP^2	0.00319***	-0.000722***	0.00420***
	(0.001)	(0.000)	(0.000)
Short Run Equation			
ECT	-0.0680**	-0.121***	-0.117***
	(0.032)	(0.020)	(0.031)
$\Delta_{t-1}Def$	1.189***	1.110***	1.123***
	(0.066)	(0.041)	(0.061)
$\Delta_{t-2}Def$	-0.488***	-0.414***	-0.409***
	(0.073)	(0.039)	(0.057)
ΔGDP	-0.00000916	-0.0105	-0.0541*
	(0.037)	(0.026)	(0.029)
$\Delta_{t-1}GDP$	0.0235	0.00316	-0.0186
	(0.034)	(0.035)	(0.015)
$\Delta_{t-2}GDP$	0.0226	-0.0902	
	(0.019)	(0.061)	
ΔGDP^2	-0.00022	0.000577	0.00267*
	(0.003)	(0.002)	(0.001)
$\Delta_{t-1}GDP^2$	-0.00163	-0.0000718	0.000964
	(0.003)	(0.002)	(0.001)
$\Delta_{t-2}GDP^2$	-0.00184	0.00666	
	(0.002)	(0.004)	
$CS\ Def$	-0.0456*	0.0817	0.0227
	(0.025)	(0.060)	(0.145)
$CS\ GDP$	0.00646	-0.00304	0.0677**
	(0.006)	(0.010)	(0.029)
$CS\ GDP^2$	-0.000599	0.000159	-0.00340**
	(0.001)	(0.001)	(0.001)
$Constant$	-0.00829	0.00713	-0.288**
	(0.018)	(0.040)	(0.139)
Observations	694	2,396	1,105
ARDL structure	(3,3,3)	(3,3,3)	(3,2,2)

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. The lag orders of the ARDL have been selected according to AIC and BIC by considering a maximum lag order of 3. The ARDL has been augmented by including cross-sectional means (CS) of the variables in the short run equation.

Table 3.29 *Enlarged EKCd model with PMG estimator (CS-ARDL)*

Long Run Equation	***Low Income***	***Middle Income***	***High Income***
GDP	-0.110***	0.0272***	-0.0301***
	(0.018)	(0.004)	(0.010)
GDP^2	0.0100***	-0.00165***	0.00111**
	(0.002)	(0.000)	(0.001)
Agr	0.0223**	0.000516	0.000588
	(0.010)	(0.001)	(0.001)
Pop	0.152***	0.0304***	-0.0607***
	(0.027)	(0.002)	(0.008)
Trd	0.00299***	0.000478***	0.000612**
	(0.001)	(0.000)	(0.000)
Short Run Equation			
ECT	-0.109*	-0.239***	-0.140***
	(0.058)	(0.024)	(0.038)
ΔGDP	-0.0549	0.00376	0.011
	(0.073)	(0.140)	(0.081)
ΔGDP^2	0.00403	-0.00148	-0.000886
	(0.006)	(0.010)	(0.004)
ΔAgr	-0.000887	0.00173	-0.00235
	(0.006)	(0.004)	(0.002)
ΔPop	0.468	-0.171	-0.0499
	(0.389)	(0.170)	(0.082)
ΔTrd	-0.000357	-0.000322	0.000375
	(0.000)	(0.000)	(0.001)
$CS\ Def$	0.452*	0.418*	0.297
	(0.232)	(0.238)	(0.406)
$CS\ GDP$	-0.00678	0.0188	0.0568
	(0.044)	(0.039)	(0.088)
$CS\ GDP^2$	0.000642	-0.00119	-0.00285
	(0.004)	(0.002)	(0.005)
$CS\ Agr$	-0.0224	-0.0011	0.000563
	(0.022)	(0.009)	(0.005)
$CS\ Pop$	-0.0217*	-0.00498	0.00417
	(0.012)	(0.006)	(0.007)
$CS\ Trd$	0.00177**	-0.00046	-0.000202
	(0.001)	(0.002)	(0.002)
$Constant$	0.00148	-0.0966	-0.258
	(0.132)	(0.145)	(0.423)
Observations	719	2,386	1,152

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. The ARDL has been augmented by including cross-sectional means (CS) of the variables in the short run equation.

rates. Trade openness now has a positive relationship with deforestation, conversely to previous results, stressing out how in long-run perspective a freer trade and more liberalization would generally sharpen deforestation rather than reduce it, especially in low income economies. Eventually, by looking at the ECTs, even in this case they are quite low (11% for low, 24% for middle, and 14% for high income), but the level of significance for the first group is quite low. Hence, the adjustment to the long run equilibrium proposed by the model is not particularly strong, then it is reasonable to expect other fact that plays a role for these countries such as macroeconomic instability, civil wars, and governments turmoils.[66]

In conclusion, results confirm the presence of cointegration among the variables under exams, then between deforestation rates and income per capita even if the TPs for middle income—which ranges approximately between US$ 3,800 and 7,000, is quite different compared with previous results.[67] Nonetheless, the apparently "weak robustness" of these TPs (and consequently also the FTs) is easily encountered in other studies on the EKC which performed different models (*e.g.* Mazzanti and Musolesi, 2013). In fact, coefficients often changes of less than one hundredth, but results, especially when previously expressed in logarithms, tend to change remarkably. The PMG estimation here proposed performed a more advanced technique in the study of the EKCd whose results evidenced different TPs and relationship with deforestation of some control variables compared with results in Sections 3.2 and 3.3. Despite limitations, this is the only study in the EKCd's literature which implemented this methodology and assessed the issue of cointegration rather than just stationarity (*e.g.* Leblois *et al.*, 2017; Ogundari *et al.*, 2017). Therefore, these last results should be more reliable respect with those obtained from a static panel model.

3.6 Concluding remarks

This chapter represented the conclusion of the research developed around the unresolved question of the possible existence of the EKC in the case deforestation. Here the theoretical background retraced in the first chapter and the reconstruction

[66]Both models presented in Tables 3.28 and 3.29 have been performed even with the MG estimator. However, by conducting a Hausman test between the two models (Hoechle, 2007) the PMG estimator has always been preferred as efficient estimator.

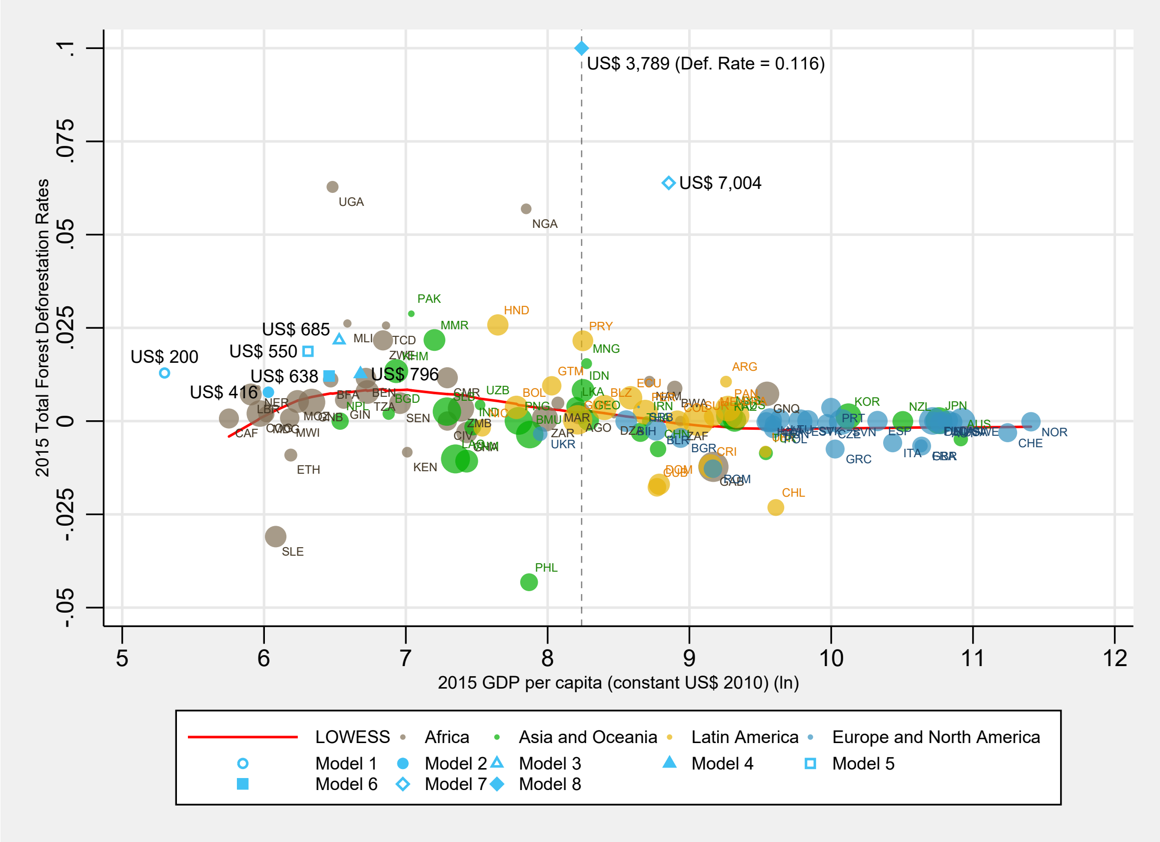
[67]They are more in line with other results presented in the literature, for example, Bhattarai and Hammig (2001) and Culas (2012), even if these studies clustered the countries by regions.

of forest cover data in the second chapter blended together in a more empirical approach.

The cross-country analysis proposed implemented both static and dynamic panel data techniques. Results concluded for an U-shape relationship for low and high income economies while a reverse U-shape curve is found for the middle income group. Therefore, the poorest countries tend to increase deforestation rates with higher levels of GDP while the shape for richest countries has to be interpreted as the achievement of the maximum level of reforestation (negative deforestation) rates rather than a return of deforestation with high levels of GDP—even though this possibility can not be excluded *a priori*. However, despite these functional forms are preserved along the models implemented, results of the TPs change due to model specification and the inclusion of control variables (agricultural area, population density, trade openness, and level of institutions). In the static model, where a simple FE approach has been implemented, for low income the TP falls between US$ 260 and 280, for middle income between US$ 200 and 800 while for the last group the range is between US$ 1,770 and 9,600. Robust estimations show less significance in GDP coefficients, but a general EKC pattern among the three income groups emerges: increasing deforestation rates for low, decreasing for middle, and U-shape for high income economies. Moreover, even the FT changes among models and for middle income economies it remarkably rises from US$ 5,636 (the model with only GDPs terms as right-hand variables) up to US$ 98,000 (when all additional variables are considered).

The specific characteristic of the panel considered, with both N and T dimensions large, could rise problems of spurious regressions with static models. Therefore, after testing for stationarity and cointegration, the dynamic estimator of the PMG has been implemented. This represented the first attempt to investigate the EKCd with this kind of approach. The three functional forms remained unchanged with the following TP: between US$ 240 and 420 for low, between US$ 3,700 and 7,000 for middle, between US$ 18,860 and 766,800 for high income economies. In this last case the value would be completely implausible suggesting a continuum phase of reforestation for the most developed group, instead. Moreover, agricultural area is positively associated with deforestation for low income while is not significant for the middle income group. Population density as well spurs deforestation for both low and middle groups but has a negative effect in the high income group. Eventually, trade openness has a positive effect on deforestation in all three groups, conversely to what obtained in the simple FE model.

Figure 3.11 *Deforestation rates and GDP per capita in 2015 with EKCd's turning points*



Notes: LOWESS function, bandwidth = 0.5; the bubble size represents the percentage of forest cover area in 2015; Model 1 refers to Table 3.2 (basic EKCd model, TP for middle income economies), Model 2 to Table 3.7 (basic EKCd model with cubic formulation, first TP), Model 3 to Table 3.10 (EKCd model with additional control variables, TP for middle income economies), Model 4 to Table 3.12 (EKCd model with additional control variables except *Ins*, TP for middle income economies), Model 5 to Table 3.14 (EKCd model with additional control variables and cubic formulation, first TP), Model 6 to Table 3.15 (EKCd model with additional control variables except *Ins* and cubic formulation, first TP), Model 7 to Table 3.28 (dynamic EKCd model, TP for middle income economies), and Model 8 to Table 3.29 (dynamic EKCd model with additional control variables, TP for middle income economies).

The Figure 3.11 attempts to summarize the main TPs obtained from the models performed along this chapter. Values refer to the last available year of the considered panel data, 2015, thus able to empathize the current relation between deforestation rates (vertical axis) and economic growth (GDP per capita on the horizontal axis). Countries are regional-divided by colors while the bubble's size associated to each country reflects the percentage of forest cover. The red LOWESS line follows the reverse U-shape of the EKCd even if the second TP is hardly identifiable. African countries, especially those of the Sub-Saharan area, have the lowest GDP levels as well as higher deforestation rates. They are followed by Asian and Latin American countries. Eventually, European and North American countries, the most industrialized of the panel, host the right-side of the graph with high income levels and low or negative deforestation rates. Along the EKCd path, four countries clearly appears as outliers, Nigeria and Uganda for deforestation while Philippines and Sierra Leone for reforestation. The Figure 3.11 reports also the EKCd's peaks identified by the different models performed with the corresponding levels of deforestation rates. The static models (from Model 1 to 6) lie in the left-side of the graph suggesting how most of the countries are now undertaking the decreasing phase of the EKCd or even the reforestation path. However, the TPs identified by the dynamic models (Models 7 and 8) are far more higher reducing the amount of countries that have overcome the EKCd.[68] By considering the last and more complete Model 8—whose TP is identified by the dotted line—, more than half of the countries in the sample now host the decreasing side of the EKCd while African and Asian countries still have to reach their own TP along this path.

In conclusion, results seem to evidence a general EKCd pattern among the considered countries even if TPs and FTs changes within the implemented models. However, results suggest how a particular attention should be focused on less developed countries since the U-shape curve suggests how their future development seems to be associated with further forest depletion. Moreover, the attention within the EKCd should be focused not only on the achievement of the notorious turning point, but also the effective achievement of a zero deforestation goal. In fact, the "distance" between the EKCd's peak and the FT may be so large that forests would be irretrievably affected. Henceforth, efforts not only to flatten out the EKCd but to shift it backward to the left are undoubtedly necessary. Eventually, this chapter could cautiously provide an humble and positive answer to Hyde's question concerning the possible existence of the EKCd. Nonetheless, the presented work for sure can not be considered free of limitations and flaws, both from data and econometrics perspectives. Therefore, further investigations can help in advance and enhance the work done so far.

[68]Note how the corresponding deforestation levels for the two dynamic models are remarkably out or range. In fact, due to the specific structure of PMG models, it is not possible to identify an effective level of the response variables (deforestation rates) corresponding to the TPs.

Conclusions

THE *Environmental Kuznets Curve* (EKC) still represents one of the leading theories among environmental economists, continuously addressed and investigated from a plethora of different perspectives. However, among this wide literature deforestation received an undertone attention. It is not a case that Hyde (2014) considers the EKC an unresolved question in forestry economics. Therefore, this work attempted to provide and exhaustive answer to the possible existence of an inverse U-shape relationship between economic growth and deforestation.

The analysis developed in Chapter 1 proposed theoretical reconciliation of three different theories: the *Forest Transition* (FT), the *Environmental Kuznets Curve for deforestation* (EKC) and the competing land use model *à la* von Thünen of the *Forest Development Path* (FDP). The two curves of the EKCd and the FT could be investigated simultaneously, linked by the three phases of the FDP, assuming a continuous economic growth over time. Differently from the common "image" of the EKC for pollutants, such as CO_2, in the case of deforestation it is possible to theorize two different turning points (TP) along the curve. The former, which is the classical goal of the EKCd, thus where deforestation rates start to decrease until the zero level of deforestation, or rather the occurrence of the FT. The latter, conversely, occurs within the negative quadrant of the curve, representing the maximum level of reforestation rates achievable. Low income economies are expecting to lie along the increasing slope of the EKCd between phases I and II of the FDP. Middle income economies are more likely to lie between the core TP of the EKCd, achievable during the phase III of the FDP, and the occurrence of the FT. Eventually, high income economies, which experienced their FT in the past, are more likely to host the section under the level of zero deforestation, around the second theorized TP of the EKCd.

The analysis proposed in Chapter 3 has been carried out by means of panel data techniques over 114 countries divided into three clusters: low, middle, and high income economies. Data on total forest cover has been properly reconstructed starting from data provided by the last FAO's *Forest Resource Assessment* (FRA) of 2015 in Chapter 2. In the static model with only GDP and GDP squared as right-hand variables, results show a U-shape curve for low income, a reverse U-shape for middle, and another U-shape, but in the quadrant of reforestation rates, for high income economies. Therefore, while low income countries rise their deforestation rates after a GDP of US$ 280, the middle income group shows a decreasing path after the peak of US$ 200. Regarding the group of more advanced economies, the TP places around US$ 9,600. Moreover, the FT is achieved between the range of US$ 1,450 and 5,630 for high and middle income economies, respectively. Although those values appear questionable low, cases in which countries achieved their FT at relative low income levels are easily to ascertain such as China and Vietnam. However, a robust estimation is more in line with a general conclusion where middle income are generally experiencing decreasing phase of the EKCd considering the low TP.

When the model is enlarged with additional control variables (agricultural area, population density, trade openness, and a proxy of the level of institutions), despite the EKCd continues to hold for middle income economies—but with less significance—the level at which the TP is achieved rises up to US$ 800 and the FT for middle income economies ranges now around US$ 52,000 and 98,000. Even the bottom TP for high income economies is reduced, from US$ 9,600 to a range which spans between US$ 1,770 and 2,360.

However, due to specific characteristics of the panel in exam, where both N and T dimensions are large, the issues of stationarity and cointegration of the variables have been tested—differently from the EKCd literature. Therefore, to avoid the risk of spurious regression, the dynamic model of the PMG has been implemented (augmented with cross-sectional means). The long run equilibrium identified results differently from the basic static model despite the functional form for the three income clusters hold: U-shape for low income with US$ 420 as TP, reverse U-shape for middle income with the peak equal to US$ 7,000, lastly the U-shape for high income economies with a TP equal to US$ 18,860. Furthermore, when agriculture, population, and trade openness are included in the model, the identified TPs are the following: US$ 245, 3,789, and 766,814. Hence, for high income economies the second TP would occur at improbable GDP levels meaning how their pattern would be mostly characterized by a continuous growth of reforestation rates.

Regarding the control variables, agriculture results to be positively associated with deforestation in the low income group where the competing use of land between agriculture and forest is more acute. Moreover, population density is positively related with deforestation in the low and middle income groups while the relationship is opposite for the last group of high income economies probably due to higher labor opportunity costs which drive off workers from marginal lands. Finally, trade openness results to have a positive association with deforestation rates for all income clusters, especially for the one of less developed countries. Anyway, it must be stressed how results for population density and trade openness are quite puzzled among the static and dynamic models since their coefficients' signs result to be opposite.

Results obtained by means of the PMG estimator are different from those of the static FE estimation, especially in reference to the TPs for middle income economies. The general pattern emerged from the results is slightly mixed even if within the EKC's literature studies that implemented different estimators or control variables tend to achieve quite different results—especially referred to the identification of the TP. Eventually, among the performed models, the peak of the EKCd ranges between US$ 200 and 7,000. This range is quite broad but able to contain countries which have undertaken the decreasing side of the EKCd both in early and later levels of development. In fact, while countries and theories could be ascribed within different "stages" of developments, this still remains a "relative" and "subjective" concept. Moreover, GDP per capita is just a mere proxy of the economic development rather than a core variable able to directly drive upward or downward changes in forest cover.

Limitations and further developments

Despite the fact that results tend to bring out an EKCd pattern, some flaws of the model must be stressed out and they could represents a foothold to develop further and more accurate analysis. First of all the difference in results within the various model and then a general lack of robustness from this perspective. This could be due of several reasons, such as the heterogeneity of individuals, the reconstruction of data performed, the presence of possible outliers or even structural breaks. Therefore, more advanced time-series panel data techniques could be implemented and spatial models (for more disaggregated data) or even non-parametric approaches could be intriguing roads to undertake. Furthermore, the extension of the model to other possible variables or rather proxies to take into account issues related to illegal timber market, property rights or institutions, for example, country risk data provided by the PRS Group (2017). Eventually, the possibility to control simultaneously even for regional and climatic diversification would be a useful enhancement for the investigation.

However, the main problem is certainly related to forest cover data since comparable yearly data within and between countries for considerably long time period are unavailable. The work attempted to reconstruct those data; nonetheless, this reconstruction is unavoidably affected by some degree of subjectivity or intrinsic errors related to data sources (since FAO has to take and publish data received from countries as they are or, in absence of them, proceed with some predictions). Therefore, the tough effort of a "wall-to-wall" reconstruction of forest data through satellite or remote sensing images, as suggested by Grainger (2008), is necessary in order to perform not only time-series specific countries studies but even comparable cross-countries analysis. One solution could be to rely on *land cover CCI* data of the Université Chatolique de Louvain UCL (2017) which provides satellite data over the period 1992–2016. Although from the time-series perspective the series would not be extremely favorable, its yearly accountability and the higher time-coverage respect to other satellite sources (Hansen *et al.*, 2013) could represent a valid justification to use this source of forest cover data for a further analysis of the EKCd and the FT.

Is there an EKC for deforestation?

In conclusion, the analysis developed in this chapter tried to make a reassessment of the EKCd providing a possible exhaustive answer for its existence. The conclusion for middle income countries, the largest group investigated, seems to cautiously suggest for the existence of the EKCd's shape. However, the levels at which the TP or the FT are achieved are mixed. Particular importance should be focused on the group of low income economies where specific and stronger interventions to reduce deforestation must be adopted, for example through compensations from high income economies. Moreover, an important glance must be focused on the decreasing phase of the EKCd and the achievement of the FT since this goal could require time or rather an extremely elevated level of development to occur. Thus, for middle income economies policies able to shift backward the EKCd and consequently the FT curve are needed.

Despite the alarmingly high deforestation rates registered in several tropical countries, at worldwide level a slowly reduction of forest losses from 1990 to 2015 has been clearly observed (FAO, 2015). Different tropical countries seems to have undertaken the decreasing phase of the EKCd, an hypothesis which seems verifiable for the case of deforestation despite mixed TPs. The implementation of the REDD+

policies to face climate change (UNFCCC, 2017), the goal of the SDGs in the Agenda 2030 (UN, 2015b) to stop deforestation by 2020 or the New York Declaration of Forest (UN, 2015a) to halve natural forest losses by 2020 and stop globally their losses by 2030 are all ambitious objectives and tools clearly in line with the decreasing phase of the EKCd.[69] Within this broad framework, experiences of community-based forest management (*e.g.* Gray *et al.*, 2001), agro-forestry activities (*e.g.* Mercer, 2004), or the overspread of Payments for Ecosystem Services (PES) (*e.g.* Lundberg *et al.*, 2018; Wunder *et al.*, 2018) are come to the fore and, despite positive and negative experiences, they are contributing to the reduction of forest losses in tropical areas. However, recent data from the Global Forest Watch (WRI, 2018) lifts shadows over this final goal to achieve a global FT and in general casts some doubts over the EKCd since deforestation seems to have undertaken a new negative uprising trend of the order of one football pitch each second (Carrington *et al.*, 2018). Accordingly, while the famous reverse U-shape EKC seems to be cautiously applicable to the case of deforestation, it cannot be considered yet a complete resolved question since results are not univocal among the implemented models and forest cover data represent a puzzled issues able to cast doubts over the complete testability of the EKCd.

[69] Targets of "zero deforestation" or similar terminologies are not always clear and tend to differ among civil society organizations, governments or private sectors which are in charge with those objectives. Therefore, uncertainties and doubts could arises with reference to such targets. The works of Brown and Zarin (2013) and Neeff and Linhares-Juvenal (2016) attempt to reassess these different commitments and their effective significance.

A

Table A.1 *Descriptive statistics for additional variables*

Low income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates (Natural Forest)	762	0.0093074	0.0095663	-0.0310359	0.0646377
Planted Forest (% Land)	762	0.0031815	0.0062184	0.00000121	0.0444421
Planted Forest (log)	762	-7.115112	1.945344	-13.62854	-3.113568

Middle income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates (Natural Forest)	2,302	0.0062392	0.0127609	-0.0504742	0.0757099
Planted Forest (% Land)	2,302	0.0135799	0.0220364	5.31E-08	0.1998768
Planted Forest (log)	2,302	-5.795427	2.250047	-16.75071	-1.610054

High income economies					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Deforestation Rates (Natural Forest)	1,025	-0.0035421	0.0431963	-0.3136245	0.4840862
Planted Forest (% Land)	1,025	0.097638	0.093334	0.0006067	0.3422634
Planted Forest (log)	1,025	-2.981107	1.36979	-7.407444	-1.072175

Table A.2 *EKCd model with FE for natural forest*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0264*	0.00363***	-0.00351	-0.00262***	0.00643	-0.00536***	-0.00201	-0.00675***	-0.142**	-0.00873**
	(0.016)	(0.001)	(0.009)	(0.001)	(0.005)	(0.000)	(0.007)	(0.001)	(0.064)	(0.004)
GDP^2	0.00245*		0.0000642		-0.000787**		-0.000304		0.00685**	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.003)	
Constant	0.0786*	-0.0132**	0.0298	0.0268***	0.00467	0.0481***	0.0433	0.0614***	0.726**	0.0843*
	(0.048)	(0.006)	(0.031)	(0.005)	(0.018)	(0.004)	(0.028)	(0.006)	(0.312)	(0.044)
Observations	791	791	1,264	1,264	2,595	2,595	1,331	1,331	1,038	1,038
AIC	-5525.3	-5523.5	-8408.3	-8410.2	-16632.1	-16627.6	-8286.2	-8287.7	-3698.7	-3696.3
BIC	-5511.3	-5514.1	-8392.8	-8400	-16614.5	-16615.9	-8270.6	-8277.3	-3683.9	-3686.4

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

Table A.3 *EKCd model with FE for natural forest (D-K robust st. err.)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0264*	0.00363***	-0.00351	-0.00262	0.00643	-0.00536***	-0.00201	-0.00675	-0.142	-0.00873
	(0.014)	(0.001)	(0.012)	(0.002)	(0.007)	(0.001)	(0.008)	(0.001)	(0.130)	(0.007)
GDP^2	0.00245**		0.0000642		-0.000787*		-0.000304		0.00685	
	(0.001)		(0.001)		(0.000)		(0.001)		(0.006)	
Constant	0.0786*	-0.0132***	0.0298	0.0268**	0.00467	0.0481***	0.0433	0.0614***	0.726	0.0843
	(0.043)	(0.004)	(0.046)	(0.013)	(0.026)	(0.006)	(0.033)	(0.007)	(0.661)	(0.073)
Observations	791	791	1,264	1,264	2,595	2,595	1,331	1,331	1,038	1,038

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

Table A.4 *Heteroscedasticity: Modified Wald test (enlarged model)*

	Low Income	*Middle Income*	*High Income*
Chi^2	1.20E+06	4.80E+05	3.40E+05
Prob > Chi^2	0.000***	0.000***	0.000***

Notes: Modified Wald test for groupwise heteroskedasticity. H_0 = no heteroscedasticity, $\sigma(i)^2 = \sigma^2$ for all *i*. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively.
The test has been performed on the model in the equation 3.4. Furthermore, the same test has been performed even without the variable *Ins* and conclusions do not change.

Table A.5 *Serial-correlation: Wooldridge test (enlarged model)*

	Low Income	*Middle Income*	*High Income*
F	17,110.97	4,832.31	5,094.55
Prob > *F*	0.000***	0.000***	0.000***

Notes: Wooldridge test for autocorrelation. H_0 = no first order autocorrelation. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively.
The test has been performed on the model in the equation 3.4. Furthermore, the same test has been performed even without the variable *Ins* and conclusions do not change.

Table A.6 *Cross-sectional dependency: CD test (additional variables)*

	Low Income				*Middle Income*				*High Income*			
	Agr_{it}	Pop_{it}	Trd_{it}[1]	Ins_{it}	Agr_{it}[2]	Pop_{it}	Trd_{it}	Ins_{it}[3]	Agr_{it}	Pop_{it}	Trd_{it}	Ins_{it}[3]
CD test	60.25	96.75	19.67	52.41	85.64	266.06	67.25		67.92	102.81	79.28	
p-value	0.03**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***		0.002***	0.000***	0.000***	
corr	0.621	0.989	0.229	0.491	0.295	0.774	0.225		0.516	0.707	0.666	
abs(corr)	0.691	0.989	0.363	0.634	0.583	0.848	0.394		0.67	0.764	0.712	

Notes: $H0$ = Cross-section independence CD $\sim N(0,1)$. *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively.

[1] This results has been obtained by removing from the low income group Eritrea and Ethiopia due to short time-span.

[2] This results has been obtained by removing from the middle income group Eastern European countries former members of URSS due to short time-span (Belarus, Bosnia and Herzegovina, Croatia, Georgia, Kazakhstan, Russian Federation, Serbia, Ukraine, Uzbekistan).

[3] Since this is the most unbalanced variable, it was not possible to perform the test.

Table A.7 *Enlarged EKCd model with FE for natural forest*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0272	0.00292***	-0.0492***	-0.000138	0.00321	-0.00270***	-0.0131*	-0.00211**	-0.174**	-0.0210***
	(0.019)	(0.001)	(0.014)	(0.001)	(0.006)	(0.001)	(0.008)	(0.001)	(0.076)	(0.008)
GDP^2	0.00242		0.00343***		-0.000389		0.000706		0.00794**	
	(0.002)		(0.001)		(0.000)		(0.000)		(0.004)	
Agr	0.0156***	0.0163***	0.00213	0.00168	0.0111***	0.0118***	0.0127***	0.0112***	0.0165	0.0125
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.022)	(0.022)
Pla	0.000176	0.000202	-0.000487	-0.000663	-0.00173***	-0.00176***	-0.00156***	-0.00152***	-0.0311***	-0.0310***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.004)
Pop	0.00221	0.00193	-0.00255	-0.00241	-0.00554***	-0.00570***	-0.0155***	-0.0148***	0.0692***	0.0838***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.022)	(0.021)
Trd	0.000485	0.000135	-0.00196**	-0.00268***	-0.00179***	-0.00160**	0.000321	-0.00023	0.0290***	0.0283***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)
Ins	-0.00201***	-0.00210***	-0.00202***	-0.00184***	-0.00342***	-0.00341***	-0.00590***	-0.00594***	0.00651	0.00113
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.006)	(0.005)
$Constant$	0.107*	0.0158*	0.193***	0.0199**	0.0174	0.0391***	0.0642**	0.0237**	0.775**	0.0662
	(0.059)	(0.009)	(0.049)	(0.008)	(0.022)	(0.007)	(0.031)	(0.011)	(0.359)	(0.071)
Observations	762	762	1,143	1,143	2,305	2,305	1,162	1,162	1,027	1,027
AIC	-5336.7	-5336.2	-7647.3	-7636	-14888.1	-14889	-7391.7	-7391.6	-3716.9	-3714.7
BIC	-5299.6	-5303.7	-7607	-7600.7	-14842.1	-14848.8	-7351.2	-7356.2	-3677.4	-3680.1

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

Table A.8 *Enlarged EKCd model with FE for natural forest (D-K robust st. err.)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0272*	0.00292***	-0.0492*	-0.000138	0.00321	-0.00270**	-0.0131**	-0.00211*	-0.174	-0.0210**
	(0.015)	(0.001)	(0.025)	(0.002)	(0.008)	(0.001)	(0.005)	(0.001)	(0.153)	(0.009)
GDP^2	0.00242**		0.00343**		-0.000389		0.000706**		0.00794	
	(0.001)		(0.002)		(0.001)		(0.000)		(0.008)	
Agr	0.0156**	0.0163**	0.00213	0.00168	0.0111*	0.0118**	0.0127	0.0112	0.0165	0.0125
	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)	(0.030)	(0.026)
Pla	0.000176	0.000202	-0.000487	-0.000663	-0.00173**	-0.00176**	-0.00156*	-0.00152*	-0.0311***	-0.0310***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)
Pop	0.00221	0.00193	-0.00255	-0.00241	-0.00554*	-0.00570**	-0.0155***	-0.0148***	0.0692*	0.0838*
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.040)	(0.048)
Trd	0.000485	0.000135	-0.00196*	-0.00268**	-0.00179	-0.0016	0.000321	-0.00023	0.0290**	0.0283**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.013)	(0.013)
Ins	-0.00201	-0.0021	-0.00202**	-0.00184**	-0.00342***	-0.00341***	-0.00590***	-0.00594***	0.00651	0.00113
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.003)
$Constant$	0.107**	0.0158	0.193*	0.0199	0.0174	0.0391**	0.0642***	0.0237	0.775	0.0662
	(0.051)	(0.013)	(0.100)	(0.023)	(0.033)	(0.016)	(0.021)	(0.020)	0.85	0.187
Observations	762	762	1,143	1,143	2,305	2,305	1,162	1,162	1,027	1,027

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

Table A.9 *Enlarged EKCd model with FE for natural forest (no institutions)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0328*	0.00355***	-0.0479***	0.0000176	0.00156	-0.00199***	-0.0139*	-0.000741	-0.127*	-0.0202***
	(0.019)	(0.001)	(0.014)	(0.001)	(0.006)	(0.001)	(0.008)	(0.001)	(0.065)	(0.007)
GDP^2	0.00292*		0.00335***		-0.000234		0.000846*		0.00567*	
	(0.002)		(0.001)		(0.000)		(0.000)		(0.003)	
Agr	0.0139***	0.0145***	0.00272	0.00256	0.0125***	0.0129***	0.0171***	0.0155***	0.0189	0.0133
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.022)	(0.021)
Pla	0.000147	0.000178	-0.000442	-0.000627	-0.00166***	-0.00167***	-0.00170***	-0.00165***	-0.0311***	-0.0310***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)
Pop	0.000018	-0.000444	-0.00560***	-0.00530***	-0.00985***	-0.00994***	-0.0205***	-0.0197***	0.0748***	0.0841***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.021)	(0.021)
Trd	0.000527	0.000103	-0.00161**	-0.00228***	-0.00201***	-0.00190***	-0.00159	-0.00226**	0.0274***	0.0280***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)
Constant	0.113*	0.00262	0.181***	0.0124	0.0119	0.0249***	0.0532*	0.00476	0.564*	0.0629
	(0.059)	(0.009)	(0.049)	(0.008)	(0.022)	(0.006)	(0.030)	(0.010)	(0.310)	(0.070)
Observations	762	762	1,159	1,159	2,384	2,384	1,225	1,225	1,036	1,036
AIC	-5327.2	-5325.5	-7744.8	-7734	-15412.8	-15414.4	-7786.5	-7785.5	-3759.1	-3758.3
BIC	-5294.8	-5297.7	-7709.4	-7703.7	-15372.3	-15379.7	-7750.7	-7754.8	-3724.5	-3728.6

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis.

Table A.10 *Enlarged EKCd model with FE for natural forest (no institutions, D-K robust st. err.)*

Def	*Low Income*		*Lower-Middle Income*		*Middle Income*		*Upper-Middle Income*		*High Income*	
	Quadratic	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**	**Quadratic**	**Linear**
GDP	-0.0328**	0.00355***	-0.0479*	0.0000176	0.00156	-0.00199*	-0.0139**	-0.000741	-0.127	-0.0202**
	(0.015)	(0.001)	(0.025)	(0.002)	(0.008)	(0.001)	(0.006)	(0.001)	(0.121)	(0.009)
GDP^2	0.00292**		0.00335**		-0.000234		0.000846**		0.00567	
	(0.001)		(0.002)		(0.001)		(0.000)		(0.006)	
Agr	0.0139*	0.0145*	0.00272	0.00256	0.0125**	0.0129**	0.0171**	0.0155*	0.0189	0.0133
	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.008)	(0.008)	(0.031)	(0.026)
Pla	0.000147	0.000178	-0.000442	-0.000627	-0.00166**	-0.00167**	-0.00170**	-0.00165**	-0.0311***	-0.0310***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)
Pop	0.000018	-0.000444	-0.0056	-0.0053	-0.00985***	-0.00994***	-0.0205***	-0.0197***	0.0748*	0.0841*
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	0.043	0.048
Trd	0.000527	0.000103	-0.00161*	-0.00228**	-0.00201*	-0.00190*	-0.00159	-0.00226	0.0274**	0.0280**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.013)	(0.013)
Constant	0.113**	0.00262	0.181*	0.0124	0.0119	0.0249	0.0532**	0.00476	0.564	0.0629
	(0.049)	(0.009)	(0.097)	(0.022)	(0.033)	(0.016)	(0.020)	(0.019)	(0.701)	(0.183)
Observations	762	762	1,159	1,159	2,384	2,384	1,225	1,225	1,036	1,036

Notes: *, **, *** indicate that statistics are significant at the 10%, 5%, and 1% level of significance, respectively. Standard errors in parenthesis. D-K is for Driscoll and Kraay (1998) robust standard errors. The maximum lag order considered for the autocorrelated structure is 3.

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