The influence of GDP, FDI and energy consumption on the amount of CO_2 emissions

An econometric analysis using a panel ARDL model

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Abstract

The increasing amount of greenhouse gasses in the atmosphere result in (predominantly) negative consequences for people and nature (e.g. extreme weather events and melting ice sheets). Researching the drivers of CO_2 emissions is therefore very relevant, so that better policies, to combat climate change, can be developed. The main focus of this thesis is therefore to look at the influence of foreign direct investment (FDI), gross domestic product (GDP) per capita and energy consumption on the amount of CO_2 emissions. A distinction is made between fossil fuel energy consumption and renewable energy consumption. Also three other variables are included; the share of the industry sector- and the service sector as a percentage of GDP and the share of trade as a percentage of GDP. When researching the influence of these variables on the amount of CO_2 emissions, a couple of theories and concepts are tested: the environmental Kuznets curve and the pollution haven- and halo hypothesis, as well as the scale-, composition- and technique effect. This research uses a ARDL model with an error correction term (ECT) for a panel of 16 countries over a time period of 1990 till 2014, to answer the research question of this thesis. The results of the pooled mean group estimator (PMG), show that FDI has a negative relationship with CO_2 emissions, confirming the pollution halo hypothesis. Also evidence for the EKC is found in the analysis, as well as a (predominantly) negative relationship with CO_2 emissions for renewable energy consumption and a positive relationship for fossil fuel energy consumption. Remarkable are the findings for the share of the industry sector and the share of the service sector, which is not in line with the composition effect, because a negative and positive relationship with CO_2 emissions is found, respectively.

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1. Introduction

According to the IPCC (2014), the influence of human activities on the climate is growing and causes irreversible impacts on the climate system and people. The amount of anthropogenic greenhouse gas (GHG) concentrations has never been so high, causing an increase in the temperature of both the atmosphere and the ocean. The Antarctic and Greenland ice sheets are shrinking and the sea level is rising. Since the industrial revolution, the acidity of the ocean also increased by 26%, due to the uptake of carbon dioxide (CO_2). Precipitation intensities change and the migration patterns and seasonal activities of species change as well. In many regions, climate change also has a negative impact on crop yield and therefore undermines food security and exacerbate the already existing human health problems. Lastly, there is an increase in extreme weather events going on since about 1950 (e.g. heavy precipitation, heat waves, cyclones) (IPCC 2014).

To combat all these problems, enhanced by climate change, it is necessary to investigate what the main drivers are. The fifth assessment report of the IPCC (2014) points to economic- and population growth as the most important drivers of the increase in CO_2 emissions. However, thereof the contribution attributed to population growth remained the same, while the impact of economic growth has risen sharply recently (IPCC 2014). According to Riti et al. (2017), economic growth causes an increase in GHGs, which has a negative impact on the ecosystems and leading to catastrophic impacts on the earth. However, economic growth is also very important to achieve. Living standards will increase (e.g. fewer diseases, less malnutrition) when the economy grows, which is especially important for people with low incomes (Kivyiro and Arminen 2014). However, also in the more developed countries, economic growth is a goal which is embedded in society (Friedman 2006).

Policy frameworks nowadays are therefore focussed on achieving economic growth, but at the same time reducing CO_2 emissions and stimulating sustainable energy resources (Lee 2013). This goal can be linked to the concept of green growth, which is upcoming and often used in the last decade (Jacobs 2013). The World Bank (2018, p.4) defines Green Growth as "economic growth that is efficient and sustainable in the use of natural resources and minimizes negative environmental externalities, while aiming at improving the welfare of society". Globally, the attention paid towards the reduction of carbon emissions is increasing. This is also reflected in international agreements, like the Paris Agreement, whereby countries strive to minimize the temperature increase to 2 ºC, but aspire a maximum increase of 1.5 ºC compared to pre-industrial magnitudes (Rauf et al. 2018).

The environmental Kuznets curve (EKC) corroborates that economic growth has an influence on the amount of CO_2 emissions. The EKC postulates a relationship between economic growth and pollution; when the economy grows (i.e. income per capita increases), pollution per capita will increase, which is called the scale effect (Grossmann and Krueger 1991). However, after a certain income level, there is a turning point after which pollution decreases (and income is still increasing). In other words, the relationship between economic growth and pollution can be described as an inverted-U-shaped relation (Grossman and Krueger 1991).

Many countries try to attract foreign direct investment (FDI), because there is an overall belief that it promotes economic growth in the host country (i.e. the country receiving FDI). Not only directly by capital formation, but it also induces human capital growth, strengthens the competitiveness of the host country and it stimulates the transfer of new and better technologies (Lee 2013). Since the 1990s many enterprises started to invest capital in developing countries. Nunnenkamp (2002) claims that under globalisation and the increasing openness of the market, multinationals seek for the locations were production costs are the lowest. The inflow of FDI increases production and stimulates economic growth. However, in the literature, there is no consensus about the impact of FDI on the environment. There exist two theories about the relationship between FDI and environmental pollution: the pollution haven hypothesis and the pollution halo hypothesis. The first theory states that due to weak environmental regulations in often developing countries, they have a comparative advantage in polluting production. Through this, there is inflow of FDI which leads to the increase in production (Pao and Tsai 2011; Zheng et al. 2010). In these countries, there is often a shift towards dirtier industries and in combination with higher production, this leads to more pollution (i.e. scale effect). The pollution halo hypothesis postulates that this scale effect can be outweighed two effects; cleaner technologies that will be deffused by the inflow of foreign capital (i.e. technique effect) and a shift in the composition of the economy (i.e. composition effect) (Pao and Tsai 2011; Zheng et al. 2010).

To achieve economic growth and at the same time decrease environmental pollution, it is relevant to investigate the impact of FDI and economic growth on CO_2 emissions (i.e. testing the pollution haven hypothesis, pollution halo hypothesis and the environmental Kuznets curve). More information about the causal relationships between the variables, will help when making appropriate policies (Kivyiro and Arminen 2014). However, looking at the already existing literature, there is one more variable that is often associated with CO_2 emissions and interlinked with the other two variables: energy consumption. According to Lee (2013), it is likely that FDI and economic growth influence the demand for energy. If one assumes that FDI increases economic growth, it is likely that energy demand grows as well and that therefore FDI and the increase in income impact the demand for energy (Lee 2013). However, this relationship can also be the other way around in probably more developed countries; when the economy grows, energy is expected to be used more efficiently and therefore FDI can help in reducing energy consumption (Kivyiro and Arminen 2014). Energy consumption is therefore an important variable to consider when investigating the drivers of CO_2 emissions.

Many scientific articles focus on the relationship between only two variables (e.g. EKC, pollution haven hypothesis) and do not investigate how FDI, income, and energy consumption together affect CO_2 emissions, while all these variables seem to be relevant. Therefore the research question of this thesis will be:

To what extent do FDI, income and energy consumption affect the amount of CO_2 emissions?

This research will not only contribute to the scientific literature, but will also help policymakers to combat climate change. FDI, for example, plays an important role in achieving economic growth and in policymaking (Lee 2013). It is therefore relevant to know if there is a relationship between FDI and CO_2 emissions, so (the increase of) GHG emissions can be reduced.

In this thesis, the focus will be on CO_2 emissions as an indicator of environmental pollution, because Baek and Choi (2017) designate CO_2 emissions as the main cause of global warming. Also, 78 percent of the increase in GHG emissions from 1970 till 2010, can be assigned to CO_2 emissions from industrial processes and fossil fuel combustion (IPCC 2014). Next to that, CO_2 emissions are highly correlating with other polluting emissions like nitrogen oxide and sulphur dioxide (Kivyiro and Arminen 2014). It is therefore very likely that when looking at the relationship between the variables and CO_2 emissions, this relationship also exists for other pollutants.

In the next chapter, the theory behind this nexus will be explained, concepts will be defined and important variables are discussed. Thereafter, there is a chapter which gives an overview of the variables and methods used in the already existing literature. Chapter 4 explains the econometric model, the corresponding tests and estimators that will be used in this thesis to analyse the data. The data for the different countries will be retrieved from the World Bank and both developing and more developed countries will be incorporated in the panel of 16 countries. The results of this econometric analysis will be presented in Chapter 5 and this report ends with a discussion and conclusion.

2. Concepts

Why should we investigate the effect of the three variables, FDI, income and energy consumption on a pollutant like CO_2? First of all, according to Kim (2019), the last twenty years the Environmental Kuznets Curve and also the pollution haven- and halo hypothesis are researched extensively. The former investigates the relationship between GDP and environmental pollution and the latter two look at the relationship between FDI and environmental pollution (Kim 2019). Next to that, a lot of research is conducted on the relationship between energy consumption and economic growth (Kim 2019) and the relationship between energy and environmental pollution (Zhu et al. 2016). All three variables seem to be important when researching the drivers of CO_2 emissions and should therefore be investigated together to get a better insight into the effect of each variable.

In this chapter, an overview is provided of the most important concepts and theories discussed in the literature about these relationships. The chapter starts with explaining the scale, composition and technique effect. Secondly, the concept of comparative advantage is shorty explained. The variables FDI, income and energy and their relationship with emissions will be discussed after that. Their importance will be explained based on, among others, the pollution haven hypothesis, the pollution halo hypothesis and the environmental Kuznets curve, which are the most prominent theories on the relationships between the variables. Throughout the chapter, the question arises if there are maybe more variables which should be taken into account and therefore additional variables and their relevance will be discussed. The chapter ends with a conclusion.

2.1. Scale-, composition- and technique effect

Grossman (1995), explains that there are three effects which determine the amount of emissions from production activities. These are the scale effect, composition effect and technique effect. Initially one would say that an increase in production and consumption causes an increase in emissions and depletes the natural resources of the earth. However, according to Grossman (1995, p. 19)

> *"if, along with economic growth, there comes a transformation in the structure of the world economy, as well as the substitution of cleaner and resource-conserving technologies for dirtier, resource-using technologies, then growth can continue to provide even higher standards of material living without threatening the nonmaterial aspects of human wellbeing."*

Grossman refers here to the composition and technique effect. Initially, one would argue that if output increases, pollution increases with the same rate, keeping all other things constant, which is the scale effect. However, this effect can be outweighed by the composition and technique effect. The composition effect entails that if the share of GDP from cleaner production activities increases, emissions will fall. The composition effect is also represented in Figure 1, whereby a decrease in pollution takes place when the economy shifts from an industrial economy to a service oriented economy. Sometimes, the composition effect can also have a negative influence on pollution. Tsurumi and Managi (2010) argue that if the change is, for example, from a more agriculturally based economy towards an industrial economy, this shift is towards a more energy-intensive economy and it is likely that this harms the environment. The technique effect entails that the level of emissions will fall if dirty pollution technologies will be replaced by more clean ones. This takes place, for example, due to innovation or government regulations (Grossman 1995). The scale- composition- and technique effect are also represented in Figure 1.

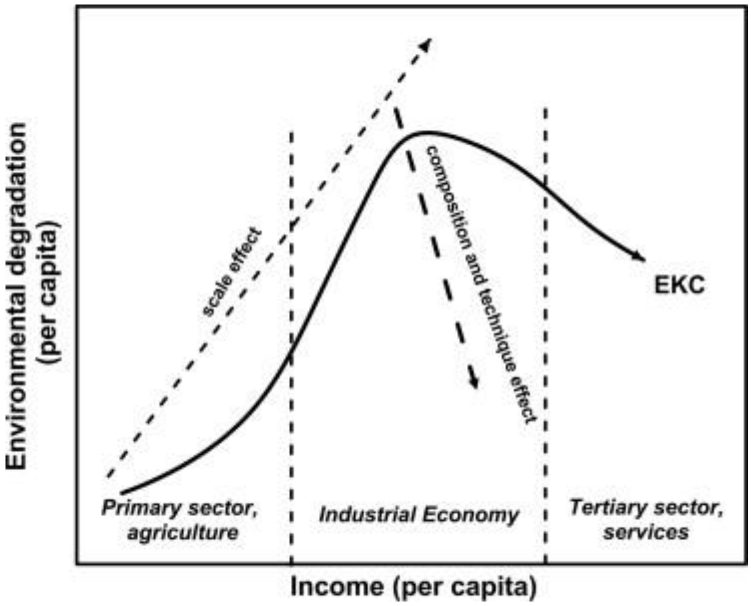

Figure 1 Graphical representation of the EKC with the scale-, composition- and technique effect (Kaika and Zervas 2013).

2.2. Comparative advantages

For the following sections, it is important to discuss and understand the concept of comparative advantages. The theory behind comparative advantages is a neo-classical trade theory. Muradian and Martinez-Alier (2001) describe that David Ricardo was the first one who showed that two countries can gain from trade. Even if a country has no absolute advantage in producing a good, this country can still gain from trade. This is the basis of the neo-classical theory: the Heckscher-Ohlin theory. The Heckscher-Ohlin theory explains the concept of comparative advantage by the abundance of production factors in a country. Which means that a country will produce the goods, at which production factors (e.g. technology, capital) are needed, where they have a relative abundance in. Both countries would gain from trade in this case (Muradian and Martinex-Alier 2001). As an example, Kohn (1998) explains that emitting-intensive countries are the countries which are endowed with the inputs, which are most needed for the production of polluting goods. In conclusion, all countries have a comparative advantage in producing a good/service and therefore all countries can gain from trade.

2.3. FDI, income and energy consumption

As mentioned before, three variables seem to be important when investigating the drivers of CO_2 emissions. This is also widely acknowledged in the literature:

> *"based on past literature, we find that energy consumption, FDI and economic growth are the main determinants of CO_2 emissions, but their impact on CO_2 emissions remains controversial." (Tang and Tan 2015 p. 447)*

Zhu et al. (2016) also affirm that economic growth and energy consumption are the most important variables that influence the environmental quality. Next to that, the increasing flows of foreign direct investment into developing countries raise the question of what influence FDI has on the environment (Zhu et al. 2016). However, these three variables are also interlinked, which makes the relationships more complicated (see Figure 2).

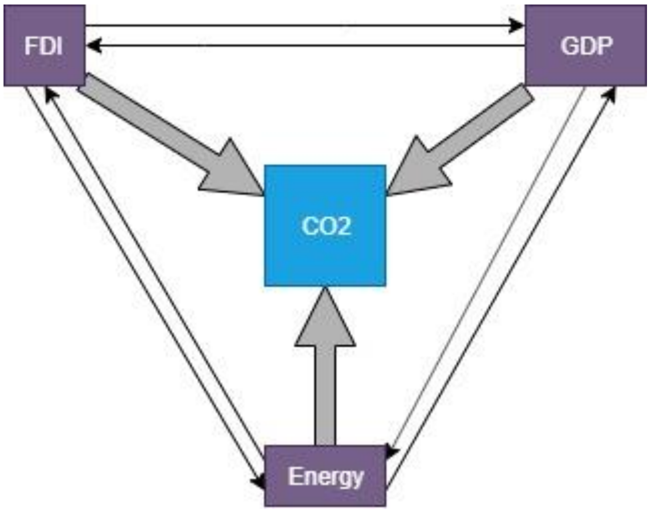

Figure 2 FDI-income-energy-CO_2 nexus

2.3.1. Foreign direct investment

Foreign direct investment (FDI) is the first variable which is related to environmental pollution. There exist two theories which postulate how FDI influences the environmental quality: the pollution haven hypothesis and the pollution halo hypothesis. The Lucas paradox, however, postulates that both theories cannot be correct, because FDI flows from developing to developed countries.

2.3.1.1. Pollution haven hypothesis

The pollution haven hypothesis postulates that polluting industries shift from developed- to developing countries, due to weaker environmental regulations in the developing countries (Levinson and Taylor 2008; Cole 2004). The difference in the stringency of environmental regulations gives developing countries a comparative advantage in polluting production (Cole 2004) and Zhu et al (2006) argue that this is the result of countries being not concerned with environmental problems and therefore not implement (enforcing) regulations for environmental protection. So the weak environmental regulations in developing countries give countries a comparative advantage for polluting production and therefore more polluting production will shift towards these countries. This means that the pollution haven hypothesis predicts that there is a negative relationship between FDI and CO_2 emissions (Zhu et al. 2016). Kim (2019) explains that this effect is exacerbated because the developed countries are obliged to reduce more GHG emissions and should therefore decrease their polluting activities. Therefore, the migration of these activities towards developing countries is enhanced.

Sarkodie and Strezov (2019) mention a broader concept which is related to the pollution haven hypothesis: the displacement effect. This means that polluting industries move towards countries with less stringent environmental regulations (i.e. the pollution haven hypothesis) and with cheaper production costs (Sarkodie and Strezov 2019). The pollution haven hypothesis can also be reinforced by the 'race to the bottom' phenomenon. Which means that under the pressure of competition, countries try to create a comparative advantage by setting their environmental regulations as low as possible (Porter 1999).

Later on, this comparative advantage can disappear. The stringency of environmental policies in developing countries can increase. That is because FDI inflows seem to increase income, and looking at the research already conducted, environmental policies become more stringent if income increases (He 2006). So developing countries will get more stringent environmental regulations, because of the inflow of FDI. A high environmental stringency can also lead to more efficient and environmental-friendly production process and encourage innovation (i.e. technique effect) (He 2006). So the increase in environmental stringency can cancel out the comparative advantage, some countries have due to weaker environmental regulations.

2.3.1.2. Pollution halo hypothesis

The pollution halo hypothesis postulates that FDI can reduce environmental pollution. This is achieved when the 'FDI corporations', so the enterprises investing in the country, diffuse their modern and environmental-friendly production techniques, which will cause a decrease in pollution (i.e. the technique effect) (Zhang and Zhou 2016).

Next to what the pollution halo hypothesis is giving as a reason, He (2006) explains that host countries (i.e. the countries receiving FDI) can also feel the urge to improve their production techniques to increase their efficiency, because of the competition with the foreign companies active in their country. This will reinforce more innovation and efficiency (He 2006). Also when FDI is directed to the service sector, the amount of emissions can decrease (i.e. the composition effect) (Zhu et al. 2016).

The Porter hypothesis also postulates that innovation can have a positive influence on emission reduction. Not because of FDI inflows, but because of regulations, that bring cost-reducing innovation (Levinson and Taylor 2008). So if you take the developed countries which have more stringent regulations, there are incentives for innovation. These innovations reduce the costs for production and therefore outweigh the comparative advantage between developed and developing countries, created by the difference in the stringency of environmental regulations (Porter and van der Linde 1995). Porter and van der Linde (1995) call this the 'innovation offsets', which means that these innovations "can not only lower the net cost of meeting environmental regulations, but can even lead to absolute advantages over firms in foreign countries not subject to similar regulations" (Porter and van der Linde 1995 p. 98).

2.3.1.3. Lucas paradox

He (2006) argues that it is questionable if the environmental regulation costs, as suggested by the pollution haven- and halo hypothesis, play a significant role in the determination of the FDI location. Looking at the case of China, for example, first there was a lot of FDI inflow into China due to their cheap labour, but more recently, this inflow is mainly to serve the growing local Chinese market and to achieve a strategic position in the Chinese market (He 2006). This suggests that environmental regulations do not give the comparative advantage for FDI flows into China.

Lucas (1990) claims that it is even the other way around: capital flows from developing to developed countries (i.e. the Lucas paradox). Alfaro et al. (2008) confirm this finding in their research. They show that from 1970 till 2000 there is more inflow of capital per capita into rich countries than into developing countries. Mainly because of the institutional quality, but also human capital and asymmetric information play a role in the direction of capital flows (Alfaro et al. 2008). This would mean that according to Lucas (1990) the pollution haven hypothesis is invalidated. The flow of capital will not be determined by the stringency of environmental regulations, but by other factors. Lucas (1990) distinguishes two groups of explanations: differences in fundamentals that affect the production structure of the economy (e.g. government policies, institutions) and international capital market imperfections (e.g. asymmetric information) (Alfaro et al. 2008).

2.3.2. Income

Growth of income, in this thesis also referred to as, gross domestic product (GDP) per capita, is associated with a change in environmental pollution. The most popular theory about this relationship is the environmental Kuznets curve (EKC).

2.3.2.1. Environmental Kuznets curve

There exists a theory about the relationship between income per capita and environmental pollution per capita: the environmental Kuznets curve, which became famous due to the article of Grossman and Krueger (1991). This theory postulates that the relationship between these variables has an inverted U-shape (see Figure 1). Which means that when income per capita increases, environmental pollution will increase as well (i.e. the scale effect). After a certain level of income, there is a turning point and environmental pollution starts decreasing, while income keeps increasing. (Pao and Tsai 2011) This can be the result of the composition effect and/or the technique effect (Grossman and Krueger 1991). According to Zhu et al. (2016), there is also evidence in the literature that this relationship is linear, N-shaped or does not even exist (Zhu et al. 2016).

2.3.3. Energy consumption

Beak (2016) emphasizes that excluding energy consumption from research on environmental pollution will lead to omitted variable bias and misleading results, because in the already existing literature there is proof that energy consumption has an impact on the environment. Zhu et al. (2016), for example, find that an increase in energy consumption will cause an increase in CO_2 emissions. According to Sarkodie and Strezov (2019), a lot of countries depend heavily on fossil fuel for their growing energy demand. It is therefore not surprising that there is a positive relationship between energy consumption and CO_2 emissions. To reduce CO_2 emissions, it is necessary to enhance energy efficiency, attract cleaner technologies and change political institutions (Sarkodie and Strezov 2019). Brazil, for example, is the largest producer of ethanol. Since 1970 the ethanol is added to gasoline, which reduced the greenhouse gas emissions of the country (Pao and Tsai 2011). For developing countries, it is often difficult to switch from fossil fuel energy- to renewable energy technologies, because they want to keep their production costs low (Sarkodie and Strezov 2019). However, it is important to keep in mind that fossil fuel energy consumption can have a different impact on the amount of CO_2 emissions than renewable energy consumption.

2.3.4. Parameter expectations

Based on the theories of the variables discussed so far, the direction of the parameters of the variables is expected to be as follows. The parameter of economic growth will be positive and if one includes a quadratic variable, that one should be negative according to the environmental Kuznets curve. Energy consumption will increase due to economic growth and therefore also increase environmental pollution. For the FDI variable, it is unclear what direction the parameter has, because of the stringency of different effects (pollution haven- or pollution halo hypothesis) (Baek and Choi 2017).

2.4. Other important drivers of CO_2 emissions

Throughout this chapter, the theories about how FDI, income and energy consumption can influence the amount of CO_2 emissions are discussed. However, other factors can also play an important role. Figure 3 summarizes this, by adding more important variables to the already discussed relationships. These other variables can influence CO_2 emissions directly or indirectly. As we already saw in the Lucas paradox, other factors, like institutional quality, directly influences FDI flows and therefore indirectly has an impact on the amount of CO_2 emissions. In this sub-section, these other variables will be discussed.

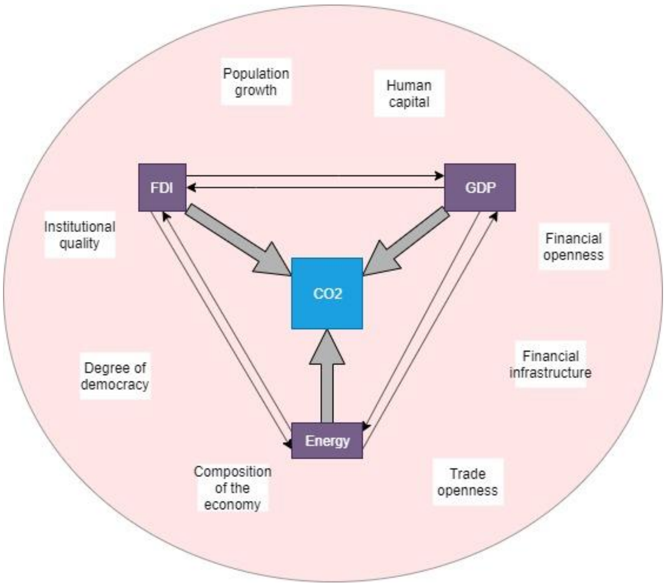

Figure 3 Broader view on the drivers of CO2 emissions

2.4.1. Composition of the economy

The composition effect, which is already discussed in this chapter, reflects the composition of the economy. So a more industrial economy, would generate a higher level of emissions than a more service-oriented economy. To investigate if this effect is significant, we can include a variable in the econometric analysis of this thesis, which reflects the composition of the economy. This variable would indirectly influence the amount of CO_2 emissions, because an increase in FDI and/or income generates CO_2 emissions, but how much emissions that will generate is depending on how polluting the sector is.

2.4.2. Trade (openness), financial development/openness, democracy, institutional failure

Trade openness can also have an impact on the amount of CO_2 emissions. Zhu et al. (2016) argue that in especially low- and high-emissions nations, CO_2 emissions can be alleviated by a higher level of trade openness. They therefore include this variable as a control variable. They also include population size, industrial structure (i.e. composition of the economy) and financial development as control variables to avoid omitted variable bias. Shahbaz et al. (2017) also researched the relationship between trade openness, economic growth and CO_2 emissions. It seems that trade openness impedes the quality of the environment, because it increases economic growth (Shahbaz et al. 2017). However some researchers argue that liberalization of trade can also improve environmental quality, because resources will be used more efficiently, it strengthens the potential of the internalization of environmental instruments and it can maintain sustainable growth (Shahbaz et al. 2017).

You et al. (2015) argue that a lot of articles ignore the influence of some variables, they argue that democracy and financial openness, can be different throughout the CO_2 emission distribution. A political variable like democracy is often included in research on the EKC, because it influences how environmental policy rules are set in a country. If a country is a democracy not only tells something about policymaking methods but can also explain institutional failures (also mentioned by Lucas (1990)). In the literature, this is also called the democracy-environmental pollution nexus. The impact on the environment is however ambiguous. Financial openness, the other variable they include, can influence environmental pollution in the sense that when financial infrastructure is improving, this can affect the efficiency of technology. However, not much research is done on this relationship (You et al.

2015). In the model of You et al. (2015) also a trade variable is included and defined as import plus export as the percentage share of GDP.

Peters et al. (2007) researched the determinants of CO_2 emissions in China, and it seems that urbanization and lifestyle changes are responsible for the increase in CO_2 emissions. These variables increase consumption and infrastructure construction and this will outweigh the increase in efficiency (Peters et al. 2007). These lifestyle changes are the result of the economic growth of China and people can therefore afford a higher consuming pattern. The infrastructure construction often increases CO_2 emissions in the early stage of economic growth, however, later on, there are more emissions from the use of the infrastructure. Also net trade has a small influence on the amount of CO_2 emissions (Peters et al. 2007). One should therefore consider if the change in consumption patterns and increase in infrastructure are variables which are important to include in an econometric analysis on CO_2 emissions.

2.4.3. Population

According to Shi (2003), population growth is also an important variable, because it is associated with an increase in CO_2 emissions. Every person has a certain demand for food, water etcetera and this all requires energy. Next to that, land use can change and deforestation can increase, due to population growth. This all can lead to an increase in CO_2 emissions (Shi 2003). However, Boserup (1981) argues that population growth gives an incentive for technological innovation, especially in the agricultural sector. Which increases the yield and the population can stay at the same level of welfare (Shi 2003). One would say that therefore population growth can induce the technique effect and maybe even lower CO_2 emissions.

An often-heard argument is that the increase in population growth comes along with an increase in consumption of energy and resources and therefore impacts the environment, as mentioned by Peters et al. (2007) in the previous sub-section. However other scholars argue that the increasing pressure on the environment stimulates technological solutions for environmental problems. But one can question if this is also the case for developing countries, where there is no money and a lack of property right, which prevents the development of these technologies (Shi 2003). In research done so far, there is proof for both arguments (Shi 2003).

2.5. Relationship between FDI, income and energy

This thesis investigates, to what extent, FDI, income and energy consumption affect the amount of CO_2 emissions. However, there is also strong evidence that these three variables interact. It is beyond the scope of this thesis, but important to keep in mind that this interaction exists. We therefore shorty describe the FDI-income and the income-energy nexus.

The relationship between FDI and economic growth seems to be bi-directional. On the one hand, countries try to attract FDI, to boost their economic growth (Lasmiraroj 2016). Take Vietnam as an example, the growth of this economy is mainly driven by the inflow of FDI (Tang and Tan 2015). On the other hand, economic growth can also attract FDI, because economic growth is associated with high-income growth and the potentially vast market (Pao and Tsai 2011). According to Lamsiraroj (2016), next to the level of the labour force, trade restrictions and beneficial investment climate, economic growth is one of the factors which influences the level of FDI inflows.

The income-energy nexus also seems to be bi-directional. It is assumed that when income grows, also the production of goods will increase, which results in a higher level of energy consumption (Pao and Tsai 2011). Ahmed and Azam (2016) describe energy as “the life-blood of growth process and ‘oxygen’ of the economy” (Ahmed and Azam 2016 p. 654). Which means that energy is crucial in achieving economic growth, because it is a production factor (Ahmed and Azam 2016). They thus argue that energy is needed to achieve economic growth.

The relationship between these two variables also depends on how depending economies are on energy.

2.6. Conclusion

Researching the drivers of CO_2 emissions is important when making appropriate policies to combat climate change. It seems that FDI, income and energy consumption are important variables, but it is ambiguous what effect they have on the level of CO_2 emissions. This is the result of the strength of different effects: the scale-, composition- and technique effect. Next to the three main independent variables, it seems that other variables also play a role in this nexus. Institutional quality, the composition of the economy and for example the population size. These do not always directly influence the amount of CO_2 emissions, but also indirectly influence the three important variables (i.e. FDI, income and energy). For this research, it is therefore important to include (some of) these variables as well. The hypotheses which are discussed in this chapter (pollution haven hypothesis, pollution halo hypothesis and the environmental Kuznets curve) will be tested and also the effect of some other important variables. This will be done with an econometric analysis, described in Chapter 4.

3. Methodology review

In Chapter 2, different theories and concepts are discussed based on the already existing literature, as well as variables which seem to be related to CO_2 emissions. These theories and variables will be investigated in this thesis with an econometric analysis. Therefore, this chapter provides an overview of the existing literature and their used methodology. In Table 1, an overview can be found. The articles used in this table also investigated a nexus between CO_2 emissions and (some of) the variables indicated as important in Chapter 2. In this chapter, first the used variables and research questions are discussed. Second, two econometric models together with the required tests and steps that are taken, will be explained. Third, some outcomes will be discussed briefly and lastly the used data sources. This chapter ends with a conclusion and the model which will be used in this thesis.

3.1. Variables and research questions

Roughly two types of research questions can be distinguished. Unidirectional research questions and bidirectional research questions. The former focuses on what impact different variables have on CO_2 emissions and the latter focuses on the (direction of the) relationship between the variables. However, this distinction is in practice not as clear-cut; the research questions which focus on CO_2 emissions as the dependent variable, also often investigate the direction of the relationship between the variables. In Table 1, Chandran and Tang (2013) for example, have a unidirectional research question, but investigate also the (direction of) relationships between all the variables. Also the articles with a bidirectional research question, sometimes focus on CO_2 emissions as the most important (dependent) variable in their results. Thus, keep in mind that the direction of the research question (i.e. uni- or bidirectional) does not immediately imply a certain method.

Most articles reviewed in this chapter also use panel data, see column 4 of Table 1. That means that the data consist of different countries (i.e. cross-sectional data) and observations through time per country (i.e. time series data) (Dougherty 2016). Zhu et al. (2016) argue that in their research a panel data framework is chosen, because it gives more information and greater efficiency in the estimation, in contrast to a single country analysis. Also, a lot of environmental problems are cross-boundary, which suggests collective response of the countries. Therefore researching the determinants of CO_2 emissions in a panel data framework seems to be an obvious choice (Zhu et al. 2016). Baek (2016) argues that a small sample size can cause problems, because the coefficients are very sensitive to model specification and can even be inefficient. Using panel data leads to more observations and can address this problem. Another advantage of panel data is that it allows for heterogeneity of the countries (Baek 2016). However, Chandran and Tang (2013) argue that through the use of time series, the analysis can detect and account for country-specific complexities (e.g. the history of energy development). The articles addressed in Table 1 do not only distinguish between panel data and time-series data, but there is also a large variety in the number of countries included in the analysis, some focus only on one country or a specific region and others include many countries.

Next to the main variables (i.e. CO_2, energy consumption, FDI, GDP), which will be included in this thesis, some articles also include other (main) variables (see column 5 of Table 1). Like financial development (Boutabba 2014) and population size (Riti et al. 2017). These two variables seem to be variables which are often included as a control variable to avoid omitted variable bias (Zhu et al. 2016; Boutabba 2014). Another example is Riti et al. (2017), who distinguish between fossil fuel energy consumption and renewable energy consumption (Riti et al. 2017). Why this distinction is important is explained already in Chapter 2. Rafiq et al.

(2016) include the added value of the agricultural- and service sector in their analysis, which captures the composition effect of the economy (see Chapter 2). There are other remarkable variables which are included in some analysis. Take Chandran and Tang (2013), they include transportation sector's energy consumption in their research, because this sector contributes to the growing amount of emissions. Trade openness (Boutabba 2014; Rafiq et al. 2016; Zhu et al. 2016) is also an often included variable, because it can, according to Zhu et al. (2016) lower carbon emissions in low and high-income countries. This variable is often measured as a ratio of import and exports to GDP (You et al. 2015; Zhu et al. 2016; Boutabba 2014). Rafiq et al. (2016) link trade openness to the pollution haven hypothesis (Chapter 2), because a higher trade openness stimulates the migration of dirty industries. Lastly, Pao and Tsai (2011) use FDI as the measure for financial development. So it is important to keep in mind that some variable can be multi interpretable.

Almost all articles transform their variables to their natural logarithms and this has different purposes. By using natural logarithms, relative (i.e. percentage) changes, instead of absolute changes are measured (Verbeek 2017). The results can in this way be interpreted as growth terms when the variables are in first differences (Pao and Tsai 2011; Tang and Tan 2015). Another advantage of transforming variables into natural logarithms is, according to Boutabba (2014), that heteroskedasticity is reduced.

Lastly, some studies have more objectives and therefore carry out multiple regressions. This is done by specifying a couple of different models (Rafindadi 2018; Rafiq et al. 2016) or by distinguishing groups of countries based on income (Baek 2016; Rafiq et al. 2016). You et al. (2015) also carry out two regressions based on two different measures of democracy.

3.2. Methods

In Table 1, it seems that one can distinguish roughly three approaches when analysing the influence of different variables on CO_2 emissions. The vector error correction model (VECM), the autoregressive distributed lag (ARDL) model and the quantile regression method with fixed effects. The latter is only shortly discussed, because it is beyond the capacity and scope of this thesis to use this model. In Figure 4 an overview is provided of the steps which are taken in the two most important models. Different tests should be performed and different estimators are used, which will also be widely discussed in this sub-section.

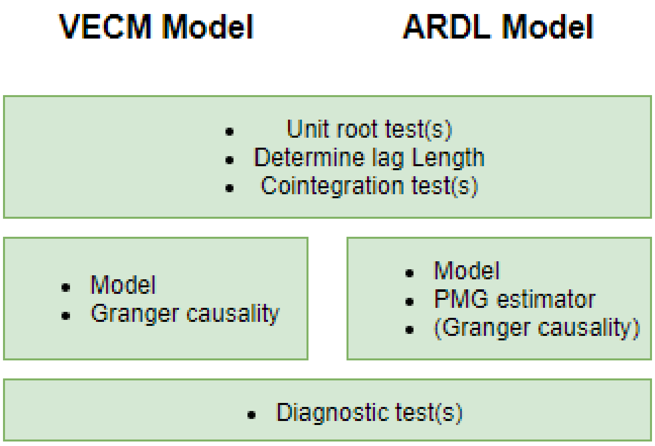

Figure 4 Overview steps within the two most important models

Table 1 Literature overview

Article	Research question	Data retrieved from	Type of data	Variables **	Methods/models/tests	Outcomes ***
Omri (2013)	Examining the nexus between CO_2 emissions, energy consumption and economic growth.	World Bank	Panel data of 14 MENA countries, 1990-2011	**CO_2, energy consumption, GDP*,** *capital stock, total labour force, total population, financial development, urbanization, trade openness.*	Cobb-Douglas production function. Simultaneous-equations models estimated by Generalized Method of Moments (GMM), *two-stage least squares (2SLS) and three-stage least squares (3SLS).*	Energy consumption ↔ GDP (+) Energy consumption → CO_2 (+) GDP ↔ CO_2 (+)
You et al. (2015)	Examine whether greater democracy and more financial openness consistently reduce emissions among the most and least emission nations.	World Bank, Marshall and Jaggers (2012), Freedom House (2011), Chinn and Ito (2008)	Panel data of 87 and 97 countries, 1985-2005	**CO_2,** Financial openness, democracy, *GDP, population size, trade openness, share of industry, freedom/polity2, Kaopen (financial openness).*	Quantile regression method with fixed effect, unit root tests, Wald test.	Democracy → CO_2 (+) in lower quantiles and (-) in upper quantiles Population size → CO_2 (+) Industrial activity → CO_2 (+) in upper quantiles GDP → CO_2 (+), Evidence for EKC
Zhu et al. (2016)	Examine the impact of FDI, economic growth and energy consumption on carbon emissions.	World Bank	Panel data of the ASEAN-5, 1998-2011	**CO_2**, FDI, GDP*, energy consumption, *population size, trade openness, industrial structure, financial development*	Quantile regression model with fixed effects, unit root tests, Johansen-Fisher cointegration test, OLS and FMOLS	FDI → CO_2 (-) in higher quantiles Energy consumption → CO_2 (+) GDP → CO_2 (-) in 95th quantile and (+) in lower quantiles Population size → CO_2 (+) in lower quantiles and (-) in upper quantiles Trade openness → CO_2 (-) No evidence for EKC
Tang and Tan (2015)	Understand the relationship between CO_2 emissions, energy consumption, FDI and economic growth.	World Bank, CEIC databases	Time series for Vietnam, 1976-2009	**CO_2, energy consumption, FDI, GDP***	VECM model, Granger causality, Johansen cointegration test, unit root tests	GDP ↔ CO_2 (+) Energy consumption → CO_2 (+) FDI ↔ CO_2 (-) Evidence for EKC

Pao and Tsai (2011)	What is the impact of both economic growth and financial development on environmental degradation.	World Bank, Energy Information Administration (EIA)	Panel data for BRIC countries, 1980-2007 (1992-2007 for Russia)	**CO_2, total energy consumption, FDI, GDP***	VECM model, Johansen Fisher test for cointegration, unit root tests, Granger causality, panel cointegration framework	CO_2 ↔ FDI (+) GDP → FDI Energy consumption → CO_2 (+) GDP ↔ CO_2 GDP ↔ energy consumption Energy ↔ FDI Evidence for EKC
Chandran and Tang (2013)	What is the impact of transportation sector's energy consumption, foreign direct investment and income on CO_2 emissions.	World Bank	Time series data for the ASEAN-5, 1971-2008	**Transportation sector's energy consumption, FDI, CO_2, GDP***	VECM model, unit root tests, cointegration and Granger causality method	GDP ↔ CO_2 (Indonesia and Thailand) GDP → CO_2 (Malaysia) Transport energy consumption ↔ CO_2 (Thailand and Malaysia) Transport energy consumption ↔ FDI (Thailand and Malaysia) FDI ↔ CO_2 (Thailand and Malaysia) No Evidence for EKC
Riti et al. (2017)	What is the impact of energy use and financial development indicators by source in the environment-growth-energy model on CO_2 emissions.	World Bank	Panel data for 90 countries, 1980-2014	**CO_2, GDP, population size, renewable energy consumption, fossil fuel energy consumption, financial development indicators**	VECM model, CADF and CIPC cointegration tests, DOLS, unit root test, Granger causality	Fossil fuel energy consumption → CO_2 (+) GDP → CO_2 (+) Renewable energy consumption → CO_2 (-) Financial development→ CO_2 (-) high and medium-income countries Financial development→ CO_2 (+), low-income countries
Boutabba (2014)	Examining the long-run equilibrium and the existence and direction of the causal relationship between carbon emissions, financial development, economic growth,	World Bank	Time series data for India, 1971-2008	**CO_2, financial development, GDP*, energy consumption, trade openness**	ARDL approach, unit root tests, Granger causality, dynamic VECM	Financial development → CO_2 (+) Financial development → energy use (+) GDP → CO_2 (+) Energy consumption ↔ CO_2 (+) Evidence for EKC

	energy consumption and trade openness.					
Rafiq et al. (2016)	What is the impact of sectoral production allocation, energy usage patterns and trade openness on pollutant emissions.	World Bank, Energy Information Administration (EIA)	Panel data of 53 countries, 1980-2010	**CO_2,** trade openness, GDP, non-renewable energy consumption, renewable energy consumption, energy intensity, service sector value added levels, agricultural sector value-added levels*, industrialisation total population*	ARDL approach, mean group estimators, pooled mean group approaches, dynamic panel models, unit root tests, Johansen Fisher test, Granger causality test	GDP→ CO_2 (+) Non-renewable energy consumption → CO_2 (+) Energy intensity→ CO_2 (+) Service sector→ CO_2 (-) Agricultural sector → CO_2 (-) Trade liberalisation → CO_2 (-) Renewable energy consumption → CO_2 (-) Evidence for EKC in high income countries
Baek (2016)	What is the effect of FDI inflows, income and energy consumption on CO_2 emissions	World Bank, UN conferences on Trade and Development (UNCTAD)	Panel data of the ASEAN-5, 1981-2010	**CO_2**, FDI, GDP*, energy consumption,	ARDL model, pooled mean group (PMG) estimator, Hausman test, unit root tests, cointegration tests	FDI → CO_2 (+) GDP → CO_2 (+) Energy consumption → CO_2 (+) Evidence for EKC
Rafindadi (2018)	Examining the effects of foreign direct investment inflows and energy consumption on environmental pollution	World Bank	Panel data for 6 GCC countries, 1990-2014	**CO_2**, energy consumption, FDI, *GDP, relative income, domestic investment, energy use*	ARDL model, pooled mean group (PMG), dynamic fixed effect (DFE), mean group (MG), unit root test, cointegration test	FDI → CO_2 (-) Energy consumption → CO_2 (+)
Mert and Bölük (2016)	What is the impact of foreign direct investment and the potential of renewable energy consumption on CO_2 emissions	World Bank	Panel data for 21 Kyoto countries, 1970-2010	**CO_2**, renewable energy consumption, FDI, *fossil fuel energy consumption, income*	ARDL approach, unit root, cointegration test, pooled mean group estimator (PMG), Granger causality	FDI→ CO_2 (-) Renewable energy consumption→ CO_2 (-) No evidence for EKC

* Real GDP per capita

Variables in **bold are dependent variables and variables in *italic* are control variables or less important in the research.

***The arrows indicate if there is a uni- or bidirection relationship. The plus (+) and minus (-) signs indicate a positive or negative relationship respectively.

3.2.1. Unit root test(s)

The first step when applying an econometric method is to look if the data contains a unit root (see Figure 4). If data contains a unit root (i.e. is non-stationary), that means that the value of X (in this case) is the same as from the previous period, but with a random error (Dougherty 2016):

$$X_t = X_{t-1} + \varepsilon_t$$

This can cause problems in further analysis. To solve this problem, first differences can be taken to make the data stationary, the data is then integrated with order one (i.e. I(1)). When the data is still non-stationary, again differences can be taken, so the data is integrated with order two (i.e. I(2)) (Dougherty 2016) and so on.

This sub-section discusses what kind of tests for unit roots are applied in the academic articles used in this chapter. However, first the most general unit root test will be discussed, to get more insight into the unit root testing procedure. This test is the Dickey-Fuller t-test.

Take this model as an example to illustrate how the test works: $Y_t = \beta_1 + \beta_2 Y_{t-1} + \varepsilon_t$

H_0: β_2=1 H_A: β_2<1

The null-hypothesis is that β_2 is one, which means that the data is non-stationary (i.e. contains a unit root) and the alternative hypothesis is that this parameter is less than one, which means that the data is stationary.

If the null hypothesis will be rejected, depends on the t-test statistic, which is formulated as follows:

$$t = \frac{\hat{\beta}_2 - 1}{s.e.(\hat{\beta}_2)}$$

This value should be compared to the critical values. If one wants to do this test for a model with more lag terms on the right-hand side, the augmented Dickey-Fuller test should be applied (Dougherty 2016).

After this short explanation of what a unit root test entails, now the many tests which are applied in the academic articles, will be discussed. A distinction is made between articles which use time-series data and articles which use panel data.

First, we start with unit root tests applied on time series data. Chandran and Tang (2013) argue that they use the Dickey-Fuller Generalised Leas Squares (DF-GLS), because of their small sample size (time-series data for 1971-2008). Also Tang and Tan (2015) adjust their critical values, because of the small sample size of their study (time-series data for 1976-2009). They first apply the Augmented Dickey-Fuller (ADF) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. However, for small samples, these tests are not very reliable, because of the so-called 'size distortion problem'. Therefore the Monte Carlo simulation based on 100,000 replications is used to generate the critical values for the unit root test, which are more reliable (Tang and Tan 2015).

Not only small sample sizes can make unit root tests less reliable. If structural breaks occur in the series, this will bias the results towards non-rejection of the null hypothesis (H_0: unit root). Therefore Boutabba (2014), uses the one- and two-break Lagrange Multiplier (LM) test statistic. This test is very reliable, because it allows for a break under the alternative and null hypothesis (Boutabba 2014).

Now we move to articles which applied unit root tests on panel data. First, Pao and Tsai (2011) distinguish two types of unit root tests. The first category is the test which looks at the common unit root, that means that there is a common unit root process across the cross-sections (i.e. the LLC and Breitung test). The other category tests the individual unit root among the cross-sections (i.e. the IPS, ADF and PP test) (Pao and Tsai 2011). These five tests are widely used for panel data in the academic literature (Mert and Bölük 2016; Rafindadi 2018; Baek 2016; Rafiq et al. 2016; Boutabba 2014).

Cross-sectional dependence can cause a bias for the panel unit root tests. Cross-sectional dependence means that the data across the countries are contemporaneously correlating (Verbeek 2017). Rafiq et al. (2016) test the existence of cross-sectional dependence with the test of Friedman, Frees and Pesaran. To minimize this problem, as well as problems associated with heterogeneity, Riti et al. (2017) apply the cross-sectional-augmented-Dickey Fuller (CADF) and the cross-sectional Im, Peseran and Shin (CIPS) stationarity tests.

3.2.2. Lag Length

Before applying the cointegration test(s), first the lag length of the variables should be chosen. Multiple tests can be applied: AIC, SBC, FPE, HQ and LR test (Tang and Tan 2015). The first two, the AIC and Schwarz Bayesian Criterion, are most commonly used in the literature (Riti et al. 2017; Chandran and Tang 2013; Boutabba 2014; Baek 2016; Rafindadi 2018).

3.2.3. Cointegration test(s)

When variables are non-stationary, spurious regressions may occur. This means that two variables seem to be related, which is not the case (Dougherty 2016). This results in inconsistent estimators and test statistics. However, this will not be the case, if these non-stationary variables have a stationary long-run relationship, this is called a cointegration relationship. So, if variables are I(1) (i.e. integrated with order one), but the linear combination of these variables is I(0), these variables are cointegrated (Maddala et al. 1998). Thus after testing for unit roots and determining the optimal lag length, the next step is testing for cointegration (see Figure 4).

Verbeek (2017) explains cointegration more mathematically; suppose that x_t and y_t are I(1). When $y_t - \beta x_t$ (for a certain β) is I(0), that means that there is cointegration. They have a shared common trend. This means that x_t and y_t do not drift too far apart in the long run. If these variables would drift far apart from each other in the long run, this would result in spurious regression. Granger (1981) also says that cointegration means that "although the two series may be unequal in the short term, they are tied together in the long run" (Granger 1981 p.129). If you put it simply, cointegration is the existence of a long-run relationship between the non-stationary variables (Verbeek 2017). In this sub-section, some cointegration tests will be discussed. First tests which are applied on time series data and after that the ones commonly used for panel data.

First, we will have a look at some articles applying cointegration tests on time series data. Tang and Tan (2015) emphasize that a multivariate cointegration technique should be used instead of a single-equation approach, because their model has more than two variables and therefore more than one cointegration relationship can exist (Tang and Tan 2015). The Johansen test seems to be the most used cointegration test. Chandran and Tang (2013) mention three important steps when performing the Johansen cointegration test. First, the optimal lag length should be chosen. Second, the constant and trend (i.e. deterministic components) should be determined, because the Johansen cointegration test is very sensitive to this choice. And lastly, there is the concern that, because of the small sample size, there is over-rejection of the null hypothesis (H_0: no cointegration). This issue is solved by adjusting the LR statistic (Chandran and Tang 2013). The Johansen cointegration test has the advantage that it is not sensitive for the choice of the dependent variable, because it is assumed that all variables are endogenous (Tang and Tan 2015). Chandran and Tang (2013) also use the Johansen and the Johansen and Juselius multivariate cointegration test to see if there is a long-run relationship. This last test also assumes that all the variables are endogenous and that the test can find more than one cointegration relationship.

Boutabba (2014) uses a very specific cointegration test; de ARDL F-bounds testing procedure, which is developed by Pesaran et al. (2001) and can only be applied for time series. In comparison with Engle and Granger and Johansen and Juselius cointegration techniques, this testing procedure has a couple of advantages. The variables can be integrated with order one and/or can be in levels. Next to that, if the research has a small sample, this method has a higher chance of detection cointegration than the method of Johansen and Juselius. And even if some independent variables are endogenous, the bounds test still gives unbiased long-run estimates (Boutabba 2014). Note however that when applying the F-statistic and the variables are integrated with order two, the test becomes invalid (Boutabba 2014). The F-test has not a standard distribution and depends on the order of integration of the variables, the number of explanatory variables in the ARDL model and if there is an intercept and/or time trend included (Boutabba 2014).

Now we move to panel data cointegration tests. The Johansen Fisher and Kao test seem to be popular methods to investigate cointegration relationships (Pao and Tsai 2011; Mert and Bölük 2016). The disadvantage of the Kao cointegration test, however, is that it assumes that the series in the panel data are homogeneous (i.e. the same). The Pedroni test considers that the series are heterogeneous across cross-sections (Riti et al. 2017). Another advantage of the Pedroni test is that it takes into account the cross-sectional dependence, which is already explained in the previous sub-section (Riti et al. 2017). Therefore Mert and Bölük (2016), Rafindadi (2018), Riti et al. (2017) and Baek (2016) all use the Pedroni test, which includes two types of cointegration test: the within dimension test (v-statistic, p-statistics, Philips-Perron statistic and Augmented Dickey-Fuller statistic), which considers common cross-sectional autoregressive estimates and between dimension tests (p-statistic, Philips-Perron statistic and the Augmented Dickey-Fuller statistic) (Riti et al. 2017). When there are mixed results from these cointegration tests, it is very common to use the error correction term, which should be negative and less than unity, to prove that there is a cointegration relationship (Baek 2016; Rafindadi 2018). This error correction term will be further explained in the following sub-sections.

3.2.4. Vector error correction model (VECM) and autoregressive distributed lag (ARDL) model

In the literature, roughly two models can be distinguished (see Figure 4); the vector error correction model (VECM) and the autoregressive distributed lag (ARDL) model. If there is cointegration, as discussed in the previous sub-section, short-run dynamics are influences and therefore an error correction mechanism should be modelled. Both models (can be) adjust(ed) to a cointegration relationship and (can) include this error correction mechanism. This is the so-called 'equilibrium error' which drives both the short- and long-run relationships in the model (Verbeek 2017; Blackburne and Frank 2007).

In addition to the error correction mechanism, which can be/is included, the VECM and ARDL model are both dynamic models. That means that the model captures causal relationships over more than one period, by including lags (Verbeek 2017). Static models have some disadvantages and therefore dynamic models are preferred. Rafiq et al. (2016) argue that static models cannot capture short- and long term relationships, which is possible in dynamic models. Also, static models assume homogeneity between variables (i.e. are the same) across cross-sections, which is not realistic in a large sample (Rafiq et al. 2016).

In this sub-section, we therefore discuss these two models: the VECM model and the ARDL model. Next to that the Granger causality test is used to investigates the direction of the causal relationships and is often applied in the VECM model approach (see Table 1). Lastly, after the ARDL model, the Pooled Mean Group (PMG) estimator will be discussed in this sub-section, because this estimator seems to be the most commonly used estimator for ARDL models.

3.2.4.1. the VECM Model

This sub-section discusses the VECM, which is a model with more than one dependent variable (captured in a vector) and the inclusion of an error correction term. The latter already implies that this model assumes that there is cointegration, as explained earlier. The VECM is discussed in more detail, because in the articles used for this methodology review, all detect cointegration in their data. However, if there is no cointegration between the variables, a vector autoregressive (VAR) system should be used, because the one-period error-correction term (ECT) (which is included to deal with the cointegration relationship) will be removed (Tang and Tan 2015).

"The vector error-correction model (VECM) is used for correcting disequilibrium in the cointegration relationship, captured by the ECT, as well as to test for long- and short-run causality among cointegrated variables" (Pao and Tsai 2001 p.687). Cointegration has implications for the behaviour of the variables in the short-run. Therefore a mechanism should be added that drives variables in their long-run equilibrium. This mechanism is represented in the ECT (Verbeek 2017). So The VECM is a model which is very useful when (a) cointegration relationship(s) exists and you want to estimate short- and long term parameters (Dougherty 2016). Another feature of the VECM is that all the variables in the VECM model are endogenous (Dougherty 2016).

The VECM model specified for Pao and Tsai (2011) is as follows and gives an idea of how this model can look like if the model is used in this thesis:

$$\begin{bmatrix} \Delta lnCO_{it} \\ \Delta lnEN_{it} \\ \Delta lnFDI_{it} \\ \Delta lnGDP_{it} \\ \Delta lnGDP_{it}^2 \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \end{bmatrix} + \sum_{p=1}^{r} \begin{bmatrix} \beta_{11p} & \beta_{12p} & \beta_{13p} & \beta_{14p} & \beta_{15p} \\ \beta_{21p} & \beta_{22p} & \beta_{23p} & \beta_{24p} & \beta_{25p} \\ \beta_{31p} & \beta_{32p} & \beta_{33p} & \beta_{34p} & \beta_{35p} \\ \beta_{41p} & \beta_{42p} & \beta_{43p} & \beta_{44p} & \beta_{45p} \\ \beta_{51p} & \beta_{52p} & \beta_{53p} & \beta_{54p} & \beta_{55p} \end{bmatrix} \begin{bmatrix} \Delta lnCO_{it-p} \\ \Delta lnEN_{it-p} \\ \Delta lnFDI_{it-p} \\ \Delta lnGDP_{it-p} \\ \Delta lnGDP_{it-p}^2 \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \end{bmatrix} ECT_{it-1} + \begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{3it} \\ \varepsilon_{4it} \\ \varepsilon_{5it} \end{bmatrix} \quad (1)$$

In this example, the vector on the left-hand side includes the dependent variables, among which the squared GDP to test the existence of the environmental Kuznets curve (see Chapter 2). Whereby i= 1,....,N, are the countries and t= 1,...T is the time period. The error term is assumed to be serially uncorrelated and the ECT_{it-1} is the lagged error correction term. The Δ is the first difference operator, because the data is assumed to be stationary when first differences are taken. The r is the lag length and Θ is the speed of adjustment (Pao and Tsai 2011). This latter parameter in combination with the lagged error correction term, represents the long-run equilibrium.

If you write the VECM as separate equations, ECM's are obtained:

$$\Delta lnCO_{it} = \alpha_1 + \sum_{p=1}^{r} \beta_{11p} \Delta lnCO_{it-p} + \sum_{p=1}^{r} \beta_{12p} \Delta lnEN_{it-p} + \sum_{p=1}^{r} \beta_{13p} \Delta lnFDI_{it-p} + \sum_{p=1}^{r} \beta_{14p} \Delta lnGDP_{it-p} + \sum_{p=1}^{r} \beta_{15p} \Delta lnGDP_{it-p}^2 + \theta_1 ECT_{it-1} + \varepsilon_{1it}$$

....

$$\Delta lnGDP_{it}^{2} = \alpha_5 + \sum_{p=1}^{r} \beta_{51p} \Delta lnCO_{it-p} + \sum_{p=1}^{r} \beta_{52p} \Delta lnEN_{it-p} + \sum_{p=1}^{r} \beta_{53p} \Delta lnFDI_{it-p} + \sum_{p=1}^{r} \beta_{54p} \Delta lnGDP_{it-p} + \sum_{p=1}^{r} \beta_{55p} \Delta lnGDP_{it-p}^{2} + \theta_5 ECT_{it-1} + \varepsilon_{5it} \quad (2)$$

3.2.4.2. Granger causality and estimators

The cointegration test, only tells something about the existence of a long-run causal relationship. The direction of this relationship can be determined by the (VECM-based) Granger causality test. Riti et al. (2017) explain Granger causality as follows; "A variable say 'x' Granger-causes a variable say 'y' if the current values of 'y' can be explained by past values of both 'x' and 'y' collaboratively" (Riti et al. 2017 p. 890). When the panel cointegration test shows that there is a long-run cointegration relationship, this means that there must be Granger causality in at least one direction (Pao and Tsai 2011).

Except for Riti et al. (2017), the other articles who apply a VECM model, do not describe how the long- and short term parameters are estimated. Riti et al. (2017) determine their long term parameter estimates by the dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS), which are preferred to OLS, because they are better able to solve the endogeneity problem and the autocorrelation of the residuals. If there is cross-sectional dependency among the series, the DOLS estimates are better (Riti et al. 2017).

3.2.4.3. The ARDL Model

The second model, the autoregressive distributed lag model, consists of two different explanatory variables (i.e. variables on the right-hand side of the model). The lagged values of the dependent variable are included and also lags of the independent variables are included in the model (Dougherty 2016). In Sub-section 3.2.2., it is already explained which tests one should use to find the optimal lag length.

One of the main reasons to use an ARDL model is that rich dynamics can be included and at the same time the problem of multicollinearity can be reduced (Dougherty 2016). A dynamic relationship means that there is a causal relationship over more than one period (Verbeek 2017). Or in other words that the model allows for changes in explanatory variables between periods (ARUP 2010). Also, long- and short-run relationships can be estimated at the same time with this model (Boutabba 2014).

Another feature of the ARDL model is that consistent estimators can be obtained if the variables are I(0), I(1) or a combination of both. However, if (some of) the variables are I(2), the results will produce spurious estimates (Baek 2016; Rafindadi et al. 2018).

The ARDL(p, q_1,....q_k) model can be specified as follows (Baek 2016; Rafindadi et al. 2018; Mert and Bölük 2016; Blackburne and Frank 2007):

$$lnCO_{it} = \mu_i + \sum_{j=1}^{p} \lambda_{ij} lnCO_{it-j} + \sum_{j=0}^{q} \delta'_{ij} X_{it-j} + \varepsilon_{it} \quad (3)$$

CO represents, in this case, the amount of CO_2 emissions and is the dependent variable. The X is a vector of all independent variables and their lags.

As explained before an error correction format should be specified (Baek 2016; Mert and Bölük 2016), if a cointegration relationship exists. The ARDL model should be rewritten with an error correction mechanism (ARUP 2010). Note that, in a single ARDL model, only one cointegration relationship can exist (Verbeek 2017).

The error correction mechanism can be specified as follows:

$$\varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) \quad (4)$$

With

$$\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}) \qquad \Theta_i = -(\sum_{j=0}^{q} \delta_{ij}/\varphi_i) \qquad \Theta_{0i} = -(\mu_i/\varphi_i)$$

This error correction mechanism, consist of the parameter φ, which measures the speed of adjustment. If this parameter is zero, there is no evidence for cointegration. Between the brackets is the error correction term, which represents the residuals of the original model (i.e. the residuals of Equation 3) (Baek 2016; Rafiq et al. 2016). The Θ_i is a vector consisting of the long-run coefficients for all independent variables.

The error-correction modelling format of the ARDL model is specified as follows (Baek 2016; Rafindadi et al. 2018; Verbeek 2017; Mert and Bölük 2016; Blackburne and Frank 2007):

$$\Delta lnCO_{it} = \mu_i + \varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta lnCO_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}^{\prime *} \Delta X_{it-j} + \varepsilon_{it} \quad (5)$$

With $\quad \varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}) \qquad \Theta_i = -(\sum_{j=0}^{q} \delta_{ij}/\varphi_i) \qquad \Theta_{0i} = -(\mu_i/\varphi_i)$

$$\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,\ldots,p-1 \qquad \delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,\ldots,q-1$$

One can see that the error correction mechanism (Equation 4) is inserted in the original ARDL model (Equation 3). The dependent variable and the variables on the right-hand side are also in first differences, because it is assumed that the variables are non-stationary in levels.

To explain the model a bit further, the p represents the lag length of the dependent variable, q the lag length of the independent variables and j is the number of time lags. X_{it} is a vector of k explanatory variables, whereby λ_{ij} and δ'_{ij} are the coefficients for the short-run effects. The long-run effects are represented in the second term on the right-hand side, the lagged error correction term. The μ_i represents the fixed effect of each country and ε_{it} the error term. The latter is assumed to be independently distributed across i and t and the regressors X_{it}, with means zero and variances larger than zero (Baek 2016; Rafindadi 2018).

3.2.4.4. Estimators

The parameters of the variables should be estimated, and looking at Table 1, roughly two estimators can be distinguished in the ARDL approach; the Pooled Mean Group (PMG) estimator and the Mean Group (MG) estimator. These estimators are thus only applied when the ARDL model is used and when the model is estimated with panel data. Which estimator to choose, depends on the presence of the homogeneity restriction. This homogeneity restriction means that the long-run coefficients are the same across the countries (i.e. homogeneous), but the short-run coefficients and the error variance can vary across the countries (i.e. heterogeneous) (Mert and Bölük 2016). When this homogeneity restricted is valid, the PMG estimator should be applied, otherwise the MG estimator should be used. This can be tested with the Hausman test (Mert and Bölük 2016; Baek 2016; Rafindadi 2018). The Mean group (MG) estimator assumes full heterogeneity and therefore when applying the MG estimator, there should be a separate ARDL model for every country (Rafindadi 2018).

All articles use the Pooled Mean Group (PMG) estimator of Pesaran et al. (1999). This estimator accounts for individual effects. Using the PMG estimator in comparison to fixed effects estimators has the advantage that parameters of the long-run effects are determined, while the short-run coefficients, the intercepts and error variances can differ among the countries (i.e. heterogeneity of the short-run coefficients and the error variance) (Baek 2016). This estimator also reduces the problem of endogeneity (Rafindadi 2018). Note however that the PMG cannot be applied when the data is I(2) (Rafindadi 2018).

Rafindadi (2018) applies next to MG and PMG, also the dynamic fixed effects technique (DFE). Which allows for heterogeneity among the intercepts, but imposes homogeneity on all coefficients and error variances (Rafindadi 2018).

Rafiq et al. (2016) argue that homogeneity is not realistic and therefore variants of the MG estimator are used: the augmented mean group (AMG) and the common correlation effects mean group (CCEMG) estimator. These estimators also have the advantage that they account for cross-sectional dependence (Rafiq et al. (2016).

3.2.5. Diagnostic test(s)

Some articles (both using VECM and ARDL models) apply diagnostic tests after short- and long-run estimates. Tests are conducted to see if the residuals are normally distributed, if there is evidence of autoregressive conditional heteroskedasticity (Tang and Tan 2015), or a specification bias (Riti et al. 2017). The latter two are tested with the Ramsey reset test and the ARCH test. The Breunsch-Godfrey Lagrangian test looks if there is no autocorrelation (Riti et al. 2017). Boutabba (2014) checks the stability of the coefficients (i.e. if there are structural breaks) by the cumulative sum (CUSUM) and the cumulative sum of squares CUSUMSQ (Boutabba 2014).

3.3. Quantile regression method (with fixed effects)

As said before, the quantile regression method (with fixed effects) is beyond the capacities and scope of this thesis. However, because it seems to be a method which is sometimes used to research this topic in the literature, the advantages and disadvantages will be shortly discussed in this sub-section.

One can apply this method if the research question is (also) focused on looking at the conditional distribution of the dependent variable (You et al. 2015). The parameters are estimated for different quantiles; from the least emitting countries to the most emitting countries. By applying the quantile regression method you avoid the problem of biased outcomes as a result of distributional heterogeneity. Also policymakers are often interested in the results of the low- and high emitting countries. For high emitting countries, it is more important to know which variables have a significant influence, because these countries should prioritize the implementation of policies to tackle environmental pollution. Another advantage of this method is that it is robust to outliers of the dependent variable and when the error term is non-normal, this regression is more efficient than an OLS regression (You et al. 2015). The problem of unobserved individual heterogeneity of countries is corrected by including fixed effects in the model (Zhu et al. 2016).

You et al. (2015) and Zhu et al. (2016) acknowledge a problem associated with panel quantile regression with fixed effect. When there is a large number of fixed effects, the incidental parameters problem can occur and estimates will be inconsistent. Koenker (2004) applies the so-called shrinkage method to deal with this problem. However, that is the reason this method is not widely used in scientific research (You et al. 2015; Zhu et al. 2016).

3.4. Outcomes

The last column of Table 1, already provides a very clear overview of the outcomes of the different analysis. In this sub-section, some outcomes are shorty discussed per econometric approach.

For the articles which use a VECM model, two of them find evidence for the EKC (Tang and Tan 2015; Pao and Tsai 2011) and one cannot find evidence (Chandran and Tang 2013). Another contradiction is found between the influence of FDI and emissions. Tang and Tan (2015) find that FDI can reduce CO_2 emissions, while Pao and Tsai (2011) find that it increases emissions. So there is evidence for both the pollution haven hypothesis and the pollution halo hypothesis (see Chapter 2). Next to that Tang and Tan (2015) find that the influence of FDI on CO_2 emission is not significant in the short-run. This can be explained by the fact that in the short term, new production techniques cannot be adapted (i.e. technique effect) (Tang and Tan 2015). It is also observed that financial development can reduce CO_2 emissions in middle- and high-income countries, while in low-income countries it increases emissions (Riti et al. 2017). Energy consumption has a positive relationship with CO_2 emissions (Pao and Tsai 2011; Tang and Tan 2015), however, Riti et al. (2017) distinguish between fossil fuel energy consumption and renewable energy consumption. The latter has a negative relationship with the amount of CO_2 emissions, which is in accordance with the theory described in Chapter 2.

The articles applying the ARDL approach, all find that GDP increases CO_2 emissions, but not all find evidence for the EKC (Boutabba 2014; Rafiq et al. 2016; Mert and Bölük 2016). There is also mixed evidence, like in the articles discussed before, on the influence of FDI on CO_2 emissions. Baek (2016) argues that FDI increases the amount of CO_2 emission, but Rafindadi (2018) and Mert and Bölük (2016) find a decrease in CO_2 emissions. Also energy consumption is associated with an increase in CO_2 emissions. However, renewable energy consumption is found to decrease the amount of emissions (Rafiq et al. 2016; Mert and Bölük 2016). More outcomes can be found in Table 1.

For the quantile regression method, the outcomes are as follows. Democracy increases CO_2 emissions in the lower quantiles, but decreases emissions in the upper quantiles. Furthermore, population size, the share of industry and income have a positive relationship with CO_2 emissions (You et al. 2015). Zhu et al. (2016) find among others that FDI lowers the amount of CO_2 emissions only in upper quantiles and that economic growth increases emissions only in lower quantiles. Energy consumption increases emissions in all quantiles (Zhu et al. 2016).

3.5. Data

A lot of scientific articles retrieved their data from the Word bank: the World Bank Development Indicators (You et al. 2015; Zhu et al. 2016; Tang and Tan 2016; Pao and Tsai 2015; Chandran and Tang 2013; Riti et al. 2017; Boutabba 2014; Rafiq et al. 2016; Baek 201; Rafindadi 2018; Mert and Bölük 2016). However, some articles use other data sources like the Energy Information Administration (EIA) (Pao and Tsai 2011; Rafiq et al. 2016) or the UN conferences on Trade and Development (UNCTAD) (Baek 2016).

3.6. Conclusion

In this chapter, an overview is provided of the used methods and tests in the existing literature. In addition to Table 1, which gives an overview of among others the used variables, methods and outcomes. The sub-sections discuss in more depth what kind of unit root tests and cointegration tests there exist and reasons to use these specific type of tests. The VECM and ARDL model are the most used models in the literature and the models are specified in this chapter. We see that using the Granger causality test is a logical step after specifying the VECM model. This test determines the direction of the causality between the variables. Articles using the ARDL model, often estimate their coefficients with the Pooled Mean Group estimator. Looking at the outcomes of the articles, it is clear that there are contradicting outcomes and therefore confirm the relevance of this thesis. After the methodology review in this chapter, the ARDL model seems to be most suitable to apply in this thesis. Especially because this thesis focusses on CO_2 as the dependent variable and not on the relationship between all variables. Therefore a single model is suitable to answer the research question. Another advantage of the ARDL model is that both variables which are (0) and I(1), can be included and still consistent estimators can be obtained. The ARDL specification can be found below, as well as the ARDL model with an error correction mechanism. The model will be discussed in more detail in the next chapter.

ARDL($p,q_1,...,q_k$) model:

$$lnCO_{it} = \mu_i + \sum_{j=1}^{p} \lambda_{ij} lnCO_{it-j} + \sum_{j=0}^{q} \delta'_{ij} X_{it-j} + \varepsilon_{it} \tag{3}$$

ARDL($p,q_1,...,q_k$) model with error correction mechanism:

$$\Delta lnCO_{it} = \mu_i + \varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta lnCO_{it-j} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{it-j} + \varepsilon_{it} \tag{5}$$

With $\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$ $\Theta_i = -(\sum_{j=0}^{q} \delta_{ij}/\varphi_i)$ $\Theta_{0i} = -(\mu_i/\varphi_i)$

$\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,\ldots,p-1$ $\delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,\ldots,q-1$

4. Methods and Data

In Chapter 3 an overview is provided of the methodology used in the already existing literature. From this review, we concluded that the ARDL model seems to fit the objective of this thesis and will therefore be used to answer the research question: "*To what extent do FDI, income and energy consumption affect the amount of CO_2 emissions?".* The tests and steps carried out in the analysis of this thesis are also largely based on the methodology review of Chapter 3. This chapter will provide in more detail how these tests and other steps will be carried out and the results will then be discussed in Chapter 5.

An overview of the different steps can be found in Figure 5, below. This chapter starts with explaining the different unit root tests and the cointegration tests, together with the specific hypothesis which are tested. After that the ARDL model will be explained and how this model will be estimated. Which variables are used for the analysis, the countries in the panel and time period of the analysis will be discussed in detail thereafter. The chapter ends with a short conclusion.

For the econometric analysis, Stata/IC 15.1 is used. The different steps of the analysis are largely based on the methodology review of Chapter 3, but are restricted by the options Stata 15.1 is providing.

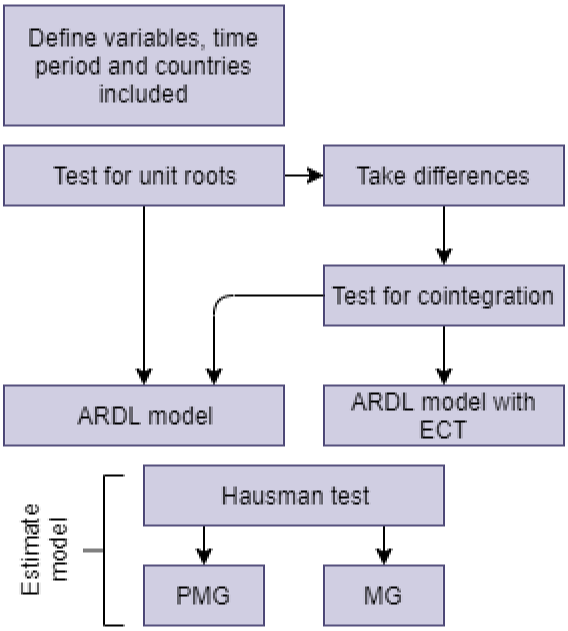

Figure 5 Graphical overview of the steps in the analysis

4.1. Unit root tests

Looking at Figure 5, the first step in the econometric analysis is conducting unit root tests. As mentioned in Chapter 3, it is important to test for unit roots, because the ARDL model can only be applied on variables that are stationary in levels or when first differences are taken (i.e. I(0) and I(1)). However, if the variables contain a unit root, even when first differences are taken, the estimates will become inconsistent. Also for the next step, testing for cointegration, it is important to know if variables are integrated with order one (I(1)), because cointegration can only occur between variables that are I(1).

First of all, Stata supports six unit root tests, which can be applied on panel data: The Levin-Lin-Chu test, Harris-Tzavalis test, Breitung test, Im-Pesaran-Shin test, Fisher type tests and Hadri Lagrange Multiplier stationary test. In Chapter 3, it became clear that five unit root tests are widely applied for panel data. The LLC and Breitung test (i.e. test for common unit roots across the cross-sections) and the IPS, ADF and PP test (i.e. test for individual unit root among the cross-sections). The latter two are part of the Fisher type test in Stata. The tests can take into account cross-sectional dependence. Cross-sectional dependence can cause problems for unit root tests and by subtracting the cross-sectional means, this problem is minimized. To sum up, the following unit root tests will be carried out:

- Levin-Lin-Chu (LLC) test,
- Breitung test,

H_0: Panels contain unit roots
H_A: Panels are stationary

- Im-Pesaran-Shin (IPS) test,

H_0: All panels contain unit roots
H_A: Some panels are stationary

- Fisher-ADF test,
- Fisher-PP test.

H_0: All panels contain unit roots
H_A: At least one panel is stationary

The unit root tests have a slightly different hypothesis that will be tested. The LLC and Breitung test will test, as explained before, for a common unit root. So their null-hypothesis also states that the panels contain unit roots. If this hypothesis can be rejected, that means that the panels are stationary. The same null hypothesis applies to the other three tests, which test for individual unit roots. However, if this null-hypothesis can be rejected, that means that some panels are stationary (IPS test) or that at least one panel is stationary (Fisher-ADF and Fisher-PP).

4.1.1. Lag length

The ARDL model is a dynamic model, which means that the relationship between variables over more than one period is taken into account. Therefore, the optimal lag length of the variables, including the dependent variable, should be determined. The optimal lag length will be obtained by the Akaike Information Criterion (AIC). The LLC and IPS unit root tests, described above, offer the possibility to obtain the optimal lag length with the AIC and at the same time perform the unit root tests. The obtained lag lengths are used for both the unit root tests and the estimation of the ARDL model.

4.2. Cointegration tests

When the data is not stationary in levels, but integrated with order one, we will test for cointegration. This is very important, because cointegration causes problems for the short-run dynamics in the model. Therefore the model should be adjusted if a cointegration relationship exists, otherwise inconsistent estimates will be obtained.

Stata supports three cointegration tests: The Kao test, Pedroni test and Westerlund test. As discussed in Chapter 3, the Kao test has some disadvantages and none of the articles used for the methodology review applied the Westerlund test. The Pedroni test is however widely used. Next to the Pedroni test, a cointegration relationship can also be identified by looking at the error correction term. When the parameter of the error correction term is negative and less than unity, there is evidence for cointegration. This error correction term will be further explained in the next sub-section.

The Pedroni test includes two different types of tests, as described in Chapter 3: the within dimension tests (for the whole panel) and between dimensions tests (for the individual countries). In Stata, the outcomes of the between dimensions tests can be obtained by including an AR parameter for each individual country. The outcomes of the within dimension tests can be obtained by including an AR parameter which is the same for the whole panel. For the cointegration tests, also the cross-sectional means will be subtracted, so the problem of cross-sectional dependence is reduced.

We will therefore analyse the existence of a cointegration relationship based on:

- The Pedroni test, consisting of:
  - Panel v-statistic,
  - Panel rho-statistic,
  - Panel PP-statistic,
  - Panel ADF-statistic,
  - Group rho-statistic,
  - Group PP-statistic,
  - Group ADF-statistic.

H_0: No cointegration
H_A: All panels are cointegrated

- The error correction term.

ECT = negative and less than unity → cointegration
ECT≠ negative and less than unity → no cointegration

The ARDL model is a single model and therefore only one cointegration relationship can be found. Therefore, the null hypothesis and alternative hypothesis of the Pedroni tests state that there is no cointegration and that all panels are cointegrated, respectively. Stata, however, only allows testing for cointegration between 7 variables. Which means that not all variables can be included at the same time. To deal with this problem, we first take out the variables which are stationary in levels (these can't be cointegrated), if possible. Next to that, different groups of variables will be tested for cointegration. For example, first the most important variables, like CO_2, GDP, FDI and energy consumption. When different groups of variables are tested, we can get an indication of whether a cointegration relationship exists or not. Lastly, when the outcomes of the Pedroni test show evidence for cointegration, we will include an ECT in the ARDL model and look if the coefficient shows indeed evidence for cointegration.

4.3. ARDL model

After the unit root tests and cointegration tests, the next step is to specify the ARDL model to estimate de coefficients of the variables. The model is very suitable to investigate how different variables affect the amount of CO_2 emissions in countries. Lagged values of the dependent variable (CO_2 emissions per capita), as well as lagged values of the independent variables, can be included in the model. Another advantage is that short- and long-run parameters can be estimated at the same time and that variables can both be I(0) and I(1). Also when there is cointegration in the data, this problem can be easily solved by inserting an error correction term (ECT). The model can be estimated in Stata with the pooled mean group (PMG) or mean group (MG) estimator, which are explained later in this chapter.

The starting point is the long-run relationship we want to investigate in this thesis:

$$lnCO_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnFDI_{it} + \alpha_4 lnFEN_{it} + \alpha_5 lnREN_{it} + \varepsilon_{it} \quad (6)$$

However, in Chapter 2 and 3, also some other variables seem to be interesting to take into account in the analysis. Therefore it is interesting to build different models, with different variables. We start with the variables, included in Equation (6) and specify three more models.

This results in the following long-run relationships:

$$lnCO_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnFDI_{it} + \alpha_4 lnFEN_{it} + \alpha_5 lnREN_{it} + \alpha_6 lnIND_{it} + \alpha_7 lnSERV_{it} + \varepsilon_{it} \quad (7)$$

$$lnCO_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnFDI_{it} + \alpha_4 lnFEN_{it} + \alpha_5 lnREN_{it} + \alpha_8 lnTRADE_{it} + \varepsilon_{it} \quad (8)$$

$$lnCO_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnFDI_{it} + \alpha_4 lnFEN_{it} + \alpha_5 lnREN_{it} + \alpha_6 lnIND_{it} + \alpha_7 lnSERV_{it} + \alpha_8 lnTRADE_{it} + \varepsilon_{it} \quad (9)$$

The exact definition of the variables included in the analysis will be explained later in this chapter. We will now have a look at the specification of the model. In the ARDL model, the variables on the right-hand side of Equations 6 till 9 (i.e. the independent variables) will be captured in a $K \times 1$ vector. As an example, for the long-run relationship of the first model (Equation (6)), the following X vector is formulated:

$$X_{it} = \begin{bmatrix} lnGDP_{it} \\ lnGDP_{it}^2 \\ lnFDI_{it} \\ lnFEN_{it} \\ lnREN_{it} \end{bmatrix} \quad (10)$$

The other three models have an X vector, with their set of independent variables.

The ARDL ($p,q_1,...,q_k$) model is used to estimate the long-run relationships, as formulated above:

$$lnCO_{it} = \mu_i + \sum_{j=1}^{p} \lambda_{ij} lnCO_{it-j} + \sum_{j=0}^{q} \delta'_{ij} X_{it-j} + \varepsilon_{it} \quad (11)$$

Keep in mind that this is the general ARDL model and that the four different models that will be estimated, all have a different X vector. The X vector is included included in the model, consisting of the (lagged) independent variables, as well as the lagged variable(s) of the dependent variable: $lnCO_{it-j}$. The number of lags for the dependent variable and independent variables are p and q, respectively. The μ_i is the country-specific intercept and ε_{it} is the error term.

This ARDL model should be re-specified if there is cointegration in the data. Cointegration causes problems in the short-run dynamics and the error correction term (ECT) should be included, so consistent estimates can be obtained. The error correction term is specified as follows:

$$\varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) \quad (12)$$

With

$$\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}) \qquad \Theta_i = -(\sum_{j=0}^{q} \delta_{ij}/\varphi_i) \qquad \Theta_{0i} = -(\mu_i/\varphi_i)$$

The parameter, φ_i, measures the speed of adjustment. So if $\varphi_i = 0$, there is no evidence for a long-run relationship (i.e. cointegration). This error correction term consists of this parameter and the lagged residuals of Equation (11), the term between brackets. The Θ_i is a vector consisting of the long term coefficients for all independent variables.

The error correction term should be included in the original ARDL model (Equation 11) to obtain consistent estimates when there is cointegration:

$$\Delta lnCO_{it} = \mu_i + \varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta lnCO_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}'^* \Delta X_{it-j} + \varepsilon_{it} \qquad (13)$$

with

$$\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}) \qquad \Theta_i = -(\sum_{j=0}^{q} \delta_{ij}/\varphi_i) \qquad \Theta_{0i} = -(\mu_i/\varphi_i)$$

$$\lambda_{ij}^* = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,\ldots,p-1 \qquad \delta_{ij}^* = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,\ldots,q-1$$

This equation also has some other differences, compared with Equation (11). The variables are now in first differences (i.e. Δ), because cointegration automatically means that the variables are not stationary in levels. The term between brackets, estimates the long-run influence of the variables, while the terms with the summation signs, capture the short-run effects. Note that the number of lags will be p-1 and q-1 in this ARDL model.

4.4. The Hausman test and the (P)MG estimator

To estimate the ARDL model, we can choose between two different estimators: the pooled mean group (PMG) estimator and the mean group (MG) estimator. In Chapter 3, the difference is already explained. Which one is the most efficient estimator, depends on the validity of the homogeneity restriction. This homogeneity restriction entails that long-run coefficients are the same for the whole panel, but short-run coefficients and error variances are country-specific. This restriction is tested by the Hausman test. Therefore first both estimators should be performed in Stata, where after the Hausman test concludes which estimator is the most suitable.

The following null-hypothesis and alternative hypothesis are formulated for the Hausman test:

H_0: (b) is consistent, (B) is consistent and efficient *or homogeneity restriction is valid*

H_A: (b) is consistent, (B) is inconsistent

(b)= mg (B)= PMG

The null-hypothesis states that the homogeneity restriction is valid, which means that the PMG estimator is the most efficient estimator to use. If the null hypothesis can be rejected, the MG estimator should be used, because the PMG estimator will generate inconsistent results.

4.5. Countries, variables and time period

For the analysis, multiple countries and a time period of 25 years is included, which means that it is a panel analysis. This choice is based on a couple of advantages of panel data. As explained in Chapter 3, panel data gives more information and greater efficiency in estimation. Panel data has a larger sample size and the estimators are therefore less sensitive to model specification. Lastly, by including a country-specific intercept, a model with panel data can allow for heterogeneity. The countries included in the analysis can be found in Table 2. The choice of the countries is first of all, based on the availability of the data for the period 1990-2014. Within this period a selection of countries is made, whereby different income levels and geographical distribution are taken into account.

Table 2 Countries included in the analysis

Income category	*Country (Stata code)*
Low-income countries	Benin (BEN)
	Senegal (SEN)
	Togo (TGO)
	Tanzania (TZA)
Low-medium income countries	Ghana (GHA)
	India (IND)
	Pakistan (PAK)
	Philippines (PHL)
Upper-medium income countries	Bulgaria (BGR)
	Mexico (MEX)
	South Africa (ZAF)
	Guatemala (GTM)
High-income countries	The Netherlands (NLD)
	New Zealand (NZL)
	Chile (CHL)
	Rep. Korea (KOR)

The data is retrieved from the World Bank and the following variables are used in the analysis:

Table 3 Original definitions and units of the variables used for the analysis

Variable	**Original definition and unit**
CO	CO_2 emissions (metric tons per capita)
GDP	GDP per capita (current US$)
FDI	Foreign direct investment, net inflows (% of GDP)
REN	Renewable energy consumption (% of total final energy consumption)
FEN	Fossil fuel energy consumption (% of total)
IND	Industry (including construction), value added (% of GDP)
SERV	Services, value added (% of GDP)
TRADE	Trade (% of GDP)

These variables are chosen, based on the availability of the data, the literature review in Chapter 2 and the variables included in other research, described in Chapter 3. The research question of this thesis already indicates that CO_2 emissions, GDP, FDI and energy consumption should be included. Whereby the latter is split up in renewable energy consumption and fossil fuel energy consumption, to see if there is a difference in the influence of the two different sources of energy. In Chapter 2, also other variables are mentioned as relevant in such an analysis. The two other variables, IND and SERV, represent the amount of GDP generated by the industry- and the service sector, respectively. These variables represent the composition effect. This effect postulates that an industry-based economy emits more CO_2 emissions, than a service-oriented economy. Therefore these variables are included to investigate the strength of this effect. Lastly, from Chapter 2 it became clear that a lot of articles include variables like trade(openness) and financial development/openness in their analysis. A trade variable can be added in a model to avoid omitted variable bias, but another argument is that more trade can also accelerate economic growth, which has an effect on the amount of CO_2 emissions. Therefore, the last variable in the analysis captures the amount of trade in a country as a percentage of GDP.

All variables will be transformed into natural logarithms, because in that way, the parameters can be interpreted as relative (i.e. percentage) changes. Expressing the variables in relative numbers can also reduce heteroskedasticity. This, however, causes problems for the FDI variable, because natural logarithms can only be taken from positive numbers, which is not always the case for FDI. Therefore we add a constant (+10) to the variable, like Baek (2016) did in his research. Also a new variable is created, the squared GDP (GDP^2), to test the environmental Kuznets curve (EKC) (see Chapter 2).

4.5.1. Descriptive statistics

In Table 4, a summary of the variables can be found for the 16 countries. For every variable, we have 400 observations, because we have data over a time period of 25 years for 16 countries. The diversity of the countries is very clear when looking at especially the minimum and maximum values of variables. If we look at TRADE for example, the minimum is 15 percent, while the maximum is 150 percent trade of the amount of GDP. That the minimum value and the maximum value are far apart from each other, is the case of every variable. However, remarkable are the values of FDI. The minimum and maximum value are far apart from each other, but the mean has a low value, as well as the standard deviation. That would imply that this variable has some strong upwards outliers.

Table 4 Descriptive statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
CO	3.501	3.773	0.078	11.967	400
GDP	6697.139	10982.79	157.061	57644.48	400
FDI	3.334	6.765	-5.007	86.611	400
REN	40.773	28.076	0.442	95.178	400
FEN	57.191	26.680	3.781	98.045	400
IND	25.768	6.393	11.983	51.275	400
SERV	50.977	9.341	26.246	69.910	400
TRADE	64.754	25.483	15.506	150.054	400

4.6. Conclusion

This chapter describes which steps are carried out in this research. Five unit root tests are applied, to see if the data is stationary in levels or first differences. When it turns out that (some of) the variables are I(1), also cointegration should be tested. The Pedroni test includes 7 different cointegration tests, which should be carried out. Next to that, we will have a look at the ECT, to see if cointegration is a problem in the data. The four different ARDL models are specified and the variables which are used. All variables are transformed into natural logarithms, so relative changes instead of absolute changes will be obtained. The model can be estimated with the PMG or MG estimator. Which estimator is the most suitable, will be tested with the Hausman test. The analysis will include a panel of 16 countries over the period of 1990 till 2014. This decision is based on the availability of the data and a representation of a variety of countries. The results of the tests and the model estimations will be widely discussed in the next chapter.

5. Results

The previous chapter discussed, which steps will be carried out in the econometric analysis of this thesis. These steps were based on Chapter 3, which described elaborately how other studies performed a similar analysis. In this chapter, the results of the tests and model estimation will be discussed. Whereby the concepts and theories explained in Chapter 2, will be linked to the outcomes of the model. Therefore this chapter will answer the research question of this thesis: *To what extent do FDI, income and energy consumption affect the amount of CO_2 emissions?* First, the outcomes of the unit root tests, the determination of the lag length and the cointegration test results will be discussed. Based on these outcomes, the final model is specified and thereafter, the outcomes of the four models will be presented. At the end of the chapter an overall conclusion is provided.

Two important concepts will be used throughout the chapter and it is therefore important to explain them beforehand: statistical significance level and p-values. For every test that is conducted and every parameter that is estimated, a test statistic and a corresponding p-value are generated. With this p-value, we can conclude if the null-hypothesis of the test can be rejected or not (i.e. if the alternative hypothesis can be accepted). One should specify a value for the level of significance (also referred to as α), which is most times 0.05. If the p-value is lower than α, the null hypothesis is rejected and if the p-value is higher than the significance level, the null hypothesis is not rejected. The hypothesis of the unit root-, cointegration- and Hausman test are already explained in the previous chapter. However, when the coefficients of the variables are determined with the PMG and MG estimator, the null hypothesis is as follows. We test if the coefficient of the parameter is different from zero (H_0: coefficient = 0). If the p-value is lower than the significance level, the null hypothesis can be rejected and proves that the variable has a significant influence on the dependent variable (Ott et al. 2010).

5.1. Unit root tests

The unit root tests, test for the existence of a unit root in de data and thus if the data is stationary. The ARDL model can be estimated with both I(0) and/or I(1) variables. It is thus important that the variables are stationary in levels or when first differences are taken (i.e. I(1)).

In Table 5, the outcomes of the five different unit root tests can be found. Some variables contain a unit root in levels, but are clearly stationary in first differences. Look at lnCO for example, all tests show that there is strong evidence for a unit root, but in first differences, the null hypothesis that the data contains a unit root, can be rejected at a 1 percent significance level. This is also the case for lnREN and lnTRADE. The outcomes are sometimes also ambiguous, when some tests reject the null hypothesis of the presence of a unit root and others show evidence that some/at least one panel(s) is/are stationary. Looking at for example lnGDP2, the tests give different results. Therefore, first differences are taken, whereafter all the tests reject the null hypothesis with a significance level of 1 percent. lnFDI is the only variable where, without any doubt, the data is stationary in levels. The tests all reject the null hypothesis with a 1 percent significance level. As emphasized by Baek (2016), the ARDL model is suitable for both variables which are stationary in levels and in first differences. The conclusion of the unit root test is therefore that all variables can be used to estimate the ARDL model and that cointegration should be tested because most variables are I(1).

Table 5 Outcomes unit root tests

	levels					First differences				
Variable	LLC	Breitung	IPS	ADF	PP	LLC	Breitung	IPS	ADF	PP
lnCO	0.03 (0.51)	2.07 (0.98)	-1.21 (0.11)	1.86 (0.97)	1.33 (0.91)	-13.71*** (0.00)	-3.29*** (0.00)	-13.11*** (0.00)	-4.89*** (0.00)	-16.53*** (0.00)
lnGDP	-8.07** (0.02)	-1.04 (0.15)	-2.59*** (0.00)	-1.82** (0.03)	-2.36** (0.01)	-11.20*** (0.00)	-6.02*** (0.00)	-12.52*** (0.00)	-11.11*** (0.00)	-16.29*** (0.00)
lnGDP2	-3.21*** (0.00)	-0.73 (0.23)	-1.90** (0.03)	-1.23 (0.11)	-1.45* (0.07)	-11.78*** (0.00)	-6.64*** (0.00)	-12.29*** (0.00)	-10.85*** (0.00)	-15.72*** (0.00)
lnFDI	-4.90*** (0.00)	-3.97*** (0.00)	-4.64*** (0.00)	-4.01*** (0.00)	-5.06*** (0.00)					
lnREN	2.69 (1.00)	4.18 (1.00)	4.53 (1.00)	4.02 (1.00)	4.16 (1.00)	12.27*** (0.00)	-5.76*** (0.00)	-12.40*** (0.00)	-8.62*** (0.00)	-15.49*** (0.00)
lnFEN	-9.01*** (0.00)	1.63 (0.95)	-5.52*** (0.00)	-2.30** (0.01)	1.48 (0.93)	-9.59*** (0.00)	-4.52*** (0.00)	-10.99*** (0.00)	-10.15*** (0.00)	-14.68*** (0.00)
lnIND	-1.71** (0.04)	-0.70 (0.24)	-1.75** (0.04)	-1.67* (0.05)	-1.03 (0.15)	-13.50*** (0.00)	-1.52* (0.07)	-12.81*** (0.00)	-6.19*** (0.00)	-16.07*** (0.00)
lnSERV	-3.31*** (0.00)	-1.62* (0.05)	-2.80*** (0.00)	-2.53** (0.01)	-2.53** (0.01)	-12.96*** (0.00)	-11.53*** (0.00)	-13.18*** (0.00)	-16.28*** (0.00)	-16.28*** (0.00)
lnTRADE	-0.94 (0.17)	-1.43* (0.08)	-0.59 (0.28)	-0.98 (0.16)	-0.71 (0.24)	-12.37*** (0.00)	-5.56*** (0.00)	-12.85*** (0.00)	-9.42*** (0.00)	-14.68*** (0.00)

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.2. Lag length

The optimal lag length is determined with the Akaike Information Criterion (AIC), which is carried out in the LLC and IPS unit root tests. The optimal lag lengths can be found in Table 6, whereby the second column shows the results of the AIC. For the other unit root tests, also lag lengths are taken into account, whereby the lag lengths are rounded, as shown in column 3 of the table. For the ARDL model with an error correction term, the lag lengths minus one should be used, which result in the lag lengths in the last column of Table 6.

Table 6 Outcomes optimal lag length

Variable	**Lag length determined by AIC**	**Lag Length used for unit root testing**	**Lag Length used for the ARDL model with ECT**
lnCO	1.81	2	1
lnGDP	1.38	1	0
lnGDP2	1.5	1	0
lnFDI	1.13	1	0
lnREN	0.75	1	0
lnFEN	2.13	2	1
lnIND	1.56	2	1
lnSERV	0.25	0	0
lnTRADE	1	1	0

5.3. Cointegration tests

The Pedroni cointegration test is applied, because a lot of variables are I(1) and therefore cointegration can be a problem. The Pedroni test, consist of four panel specific cointegration tests and three groups specific tests. Stata limits the number of variables that can be tested to a maximum of seven, through which we specified different groups of variables, to test for cointegration:

- Group 1: lnCO, lnGDP, lnGDP2, lnREN, lnFEN
- Group 2: lnCO, lnGDP, lnGDP2, lnREN, lnFEN, lnIND, lnSERV
- Group 3: lnCO, lnGDP, lnGDP2, lnREN, lnFEN, lnTRADE

The FDI variable is not included in any of the tests, because this variable is I(0) and can therefore not be cointegrated. The groups are based on the four models that are already shorty discussed in the previous chapter. The first group includes the most important variables (tested in Model 1) and the other two groups include the extra variables included in Model 2 and 3, respectively.

In Table 7, the outcomes of the Pedroni test can be found. It is clear that, irrespective of the group of variables, the outcomes of the test are ambiguous. For group 1, four tests cannot reject the null hypothesis of no cointegration and three can reject the null hypothesis, with a significance level of 5% (or less). The second group shows more evidence for cointegration, whereby five tests accept the alternative hypothesis of cointegration. The last group has four tests with a p-value lower than 0.05, and therefore accept the alternative hypothesis. In conclusion, we can say that the results of the cointegration tests are ambiguous and therefore an ECT will be included. If this ECT is negative and less than unity, this will prove the existence of cointegration.

Table 7 Outcomes cointegration tests

Cointegration test	**Group 1**	**Group 2**	**Group 3**
Panel v-statistic	-2.45** (0.01)	-3.48*** (0.00)	-2.97*** (0.00)
Panel rho-statistic	1.84** (0.03)	2.78*** (0.00)	2.40** (0.01)
Panel PP-statistic	0.06 (0.48)	-0.43 (0.34)	-0.11 (0.45)
Panel ADF-statistic	-0.26 (0.40)	-0.99 (0.16)	-0.79 (0.21)
Group rho-statistic	2.75*** (0.00)	3.84*** (0.00)	3.04*** (0.00)
Group PP-statistic	-0.28 (0.39)	-1.40* (0.08)	-1.02 (0.15)
Group ADF-statistic	-0.52 (0.30)	-1.62* (0.05)	-2.18** (0.01)

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.4. Model specification

The lag length has been determined and the Pedroni test indicates a possible cointegration relationship between the variables, now the ARDL models with ECT can be formulated.

In Chapter 4, four different models are formulated. The first model is the one with the most important variables, according to the literature described in Chapter 2. After that, we formulate model 2 and 3, whereby the most important variables are included and 2 more variables and 1 more variable, respectively. The fourth model includes all 9 variables.

The general ARDL ($p,q_1,....,q_k$) model with ECT is formulated as follows:

$$\Delta lnCO_{it} = \mu_i + \varphi_i(lnCO_{it-1} - \Theta_{0i} - \Theta'_i X_{it}) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta lnCO_{it-j} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{it-j} + \varepsilon_{it} \qquad (14)$$

with

$$\varphi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij}) \qquad \Theta_i = -(\sum_j^q \delta_{ij}/\varphi_i) \qquad \Theta_{0i} = -(\mu_i/\varphi_i)$$

$$\lambda^*_{ij} = -\sum_{m=j+1}^{p} \lambda_{im} \quad j = 1,2,\ldots,p-1 \qquad \delta^*_{ij} = -\sum_{m=j+1}^{q} \delta_{im} \quad j = 1,2,\ldots,q-1$$

The only difference between the models is the X vector, consisting of all the independent variables, and the corresponding lag lengths (see last column Table 6). Below, the 4 different X vectors for the models are formulated.

Model 1: ARDL (1,0,0,0,0,1) model, with X vector:

$$X_{it} = \begin{bmatrix} lnGDP_{it} \\ lnGDP_{it}^2 \\ lnFDI_{it} \\ lnREN_{it} \\ lnFEN_{it} \end{bmatrix} \tag{15}$$

Model 2: ARDL (1,0,0,0,0,1,1,0) model, with X vector:

$$X_{it} = \begin{bmatrix} lnGDP_{it} \\ lnGDP_{it}^2 \\ lnFDI_{it} \\ lnREN_{it} \\ lnFEN_{it} \\ lnIND_{it} \\ lnSERV_{it} \end{bmatrix} \tag{16}$$

Model 3: ARDL (1,0,0,0,0,1,0) model, with X vector:

$$X_{it} = \begin{bmatrix} lnGDP_{it} \\ lnGDP_{it}^2 \\ lnFDI_{it} \\ lnREN_{it} \\ lnFEN_{it} \\ lnTRADE_{it} \end{bmatrix} \tag{17}$$

Model 4: ARDL (1,0,0,0,0,1,1,0,0) model, with X vector:

$$X_{it} = \begin{bmatrix} lnGDP_{it} \\ lnGDP_{it}^2 \\ lnFDI_{it} \\ lnREN_{it} \\ lnFEN_{it} \\ lnIND_{it} \\ lnSERV_{it} \\ lnTRADE_{it} \end{bmatrix} \tag{18}$$

5.5. Model estimation

The models are estimated with both the mean group (MG) estimator as well as the pooled mean group estimator (PMG). Thereafter the Hausman test is applied, to see which of the two estimators is efficient. All four models and their results will be discussed in this sub-section.

5.5.1. Model 1

The results of the first model can be found in Table 8 below. We will first look at the result of the Hausman test. The chi-square statistic has a value of 0.54 with a corresponding p-value of 0.99. This means that the null hypothesis can’t be rejected. That means that the homogeneity restriction is valid and the results of the PMG estimator the most efficient. Therefore, we focus on the results of the PMG estimator. First, the ECT is statistically significant (with a significance level of 0.05) and the coefficient has a value of -0.14, which indicates that the model indeed contains a cointegration relationship. The first remarkable outcome is that in the long-run, only one variable has a significant influence on the amount of CO_2 emissions per capita. The variable of fossil fuel energy consumption has a coefficient of 0.92, which is statistically significant at a 1 percent significance level. This is in line with Chapter 2, were (fossil fuel) energy consumption is associated with an increase in CO_2 emissions. A one percent increase in fossil fuel energy consumption as a percentage of the total amount of energy consumption, means that there is 0.92 percent increase in CO_2 emissions per capita. In the short run, only renewable- and fossil fuel energy consumption have a significant influence on the amount of CO_2 emissions per capita. Whereby fossil fuel energy consumption increases the amount of CO_2 emissions and renewable energy decreases emissions. The latter is also in line with the expectations, as explained in Chapter 2.

Table 8 Outcomes Model 1

Variables	**Pooled mean group**		**Mean group**	
	Long-run	Short-run	Long-run	Short-run
ECT		-0.14^{**} (0.02)		-0.85^{***} (0.00)
$LnCO_{it-1}$		-0.10 (0.18)		0.13 (0.12)
$lnGDP_{it}$	-0.16 (0.81)	1.48 (0.12)	-0.75 (0.69)	1.34 (0.30)
$lnGDP2_{it}$	0.05 (0.29)	-0.11 (0.13)	0.12 (0.36)	-0.11 (0.25)
$lnFDI_{it}$	-0.15 (0.17)	0.00 (0.98)	-0.08 (0.62)	0.04 (0.40)
$lnREN_{it}$	0.35 (0.14)	-0.45^{*} (0.06)	0.12 (0.82)	-0.02 (0.91)
$lnFEN_{it}$	0.92^{***} (0.00)	0.82^{**} (0.01)	0.56 (0.45)	0.61^{*} (0.05)
$lnFEN_{it-1}$		0.17 (0.45)		0.09 (0.63)
Constant		-0.86^{**} (0.02)		5.49 (0.43)
Hausman		0.54 (0.99)		

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.5.2. Model 2

In Model 2, the composition effect is taken into account. Next to the most important variables (Model 1), the two variables for the percentage that the industry sector and service sector add to the total amount of GDP, are added to the model. The Hausman test, again shows that the PMG estimator is the most efficient, with a p-value of 0.98. We also see that the ECT is negative and less than unity, so this proves a cointegration relationship. Now the two extra variables are added, GDP per capita and renewable energy consumption show a statistically significant influence on the amount of CO_2 emissions per capita, while they were not significant in the previous model. Starting with the long-run effect of the variables, we see that GDP per capita has a positive relationship with CO_2 emissions per capita (i.e. increases the amount of emissions). This is in line with the scale effect, discussed in Chapter 2. We therefore can conclude that the scale effect cannot be outweighed by for example the technique effect. The fossil fuel energy consumption variable and the renewable energy consumption variable have, as expected, a positive and negative effect on the amount of emissions per capita, respectively. The other variable, which is significant in the long run, is the share of industry as a percentage of GDP. One expects that, the more industry in a country, the more emissions per capita, in accordance with the composition effect. However, the estimation shows that when the amount of industry increases by 1 percent, emissions per capita will fall with 0.56 percent. This outcome is statistically significant at a 1 percent level and is in contradiction with what is expected. Possibly, the industry sector is not as polluting as one would expect. In the short run, only fossil fuel energy consumption has a positive influence on the amount of CO_2 emissions per capita.

Table 9 Outcomes Model 2

Variables	**Pooled mean group**		**Mean group**	
	Long-run	Short-run	Long-run	Short-run
ECT		-0.22^{***} (0.00)		-1.04^{***} (0.00)
$lnCO_{it-1}$		-0.08 (0.25)		0.28^{**} (0.02)
$lnGDP_{it}$	0.40^{**} (0.01)	-0.26 (0.80)	-1.90 (0.61)	1.21 (0.63)
$lnGDP2_{it}$	-0.01 (0.28)	0.02 (0.83)	0.27 (0.29)	-0.12 (0.52)
$lnFDI_{it}$	0.01 (0.90)	-0.02 (0.70)	-0.30 (0.30)	0.06 (0.40)
$lnREN_{it}$	-0.23^{***} (0.00)	-0.29 (0.39)	1.51 (0.23)	0.15 (0.78)
$lnFEN_{it}$	1.06^{***} (0.00)	0.55^{**} (0.03)	0.55 (0.69)	0.61 (0.18)
$lnFEN_{it-1}$		0.06 (0.83)		0.05 (0.84)
$LnIND_{it}$	-0.56^{***} (0.00)	-0.12 (0.33)	-0.98 (0.50)	-0.86 (0.10)
$LnIND_{it-1}$		*0.04 (0.65)*		*-0.28 (0.17)*
$lnSERV_{it}$	0.03 (0.76)	-0.51 (0.12)	-3.28^{**} (0.02)	-1.14 (0.14)
Constant		-0.80^{***} (0.00)		18.48 (0.23)
Hausman		1.48 (0.98)		

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.5.3. Model 3

The third model adds trade as a percentage of GDP, as an extra variable on top of the variables in Model 1. Again, the null hypothesis of the Hausman test cannot be rejected, that means that the PMG is the most efficient estimator. Also the ECT is negative and less than unity, which indicates the existence of cointegration. In Table 10, the results can be found and what stands out immediately is that in the long-run, all variables have a significant influence on CO_2 emissions per capita. Starting with the variables of GDP. The outcomes are as expected when looking at the EKC. The EKC postulates an inverted U-shape, which implies that the variable for GDP per capita should be positive and GDP^2 per capita negative. This is indeed the case, as the coefficients are 1.34 and -0.07, respectively. The energy consumption coefficients are, again, as expected positive (for fossil fuel energy consumption) and negative (for renewable energy consumption). If we compare the results with the previous model, the coefficient of renwable energy consumption is almost the same, while the coefficient of fossil fuel energy consumption is more than three times smaller than in Model 2. As discussed in Chapter 2, there was no clear answer about the influence of FDI on environmental pollution as well as the influence of the amount of trade. In Table 10, we see that FDI has a small negative effect on the amount of CO_2 emissions per capita and trade has a small positive effect on the amount of CO_2 emissions per capita. The latter also confirm that trade, as a variable, should be included in such an analysis, because it shows an influence on environmental pollution. This was doubtful, because only a few articles included trade as an important variable. Lastly, in the short run, only fossil fuel energy consumption has a positive and significant influence on the amount of CO_2 emissions per capita.

Table 10 Outcomes Model 3

Variables	**Pooled mean group**		**Mean group**	
	Long-run	Short-run	Long-run	Short-run
ECT		-0.34^{**} (0.01)		-0.81^{***} (0.00)
$LnCO_{it-1}$		-0.00 (0.97)		0.12 (0.23)
$lnGDP_{it}$	1.34^{***} (0.00)	-0.03 (0.97)	-30.22 (0.33)	2.33 (0.13)
$lnGDP2_{it}$	-0.07^{***} (0.00)	-0.01 (0.93)	2.43 (0.32)	-0.18 (0.12)
$lnFDI_{it}$	-0.03^{**} (0.02)	-0.03 (0.50)	2.72 (0.33)	-0.02 (0.71)
$lnREN_{it}$	-0.22^{***} (0.00)	-0.30 (0.22)	7.68 (0.32)	0.02 (0.95)
$lnFEN_{it}$	0.29^{**} (0.01)	0.69^{**} (0.01)	-0.82 (0.56)	0.51^{**} (0.03)
$lnFEN_{it-1}$		*0.06* *(0.79)*		*-0.06* *(0.79)*
$lnTRADE_{it}$	0.09^{**} (0.01)	0.06 (0.24)	4.39 (0.30)	0.10 (0.15)
Constant		-2.03^{***} (0.00)		-2.22 (0.69)
Hausman		2.07 (0.91)		

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.5.4. Model 4

The estimation of Model 4 will show the results of all the variables discussed so far in the previous models (see Table 11). Some results are the same as seen in the previous models and others will give opposite results. Again, the Hausman test indicates that the PMG estimator is the most efficient and also the ECT has a coefficient that is negative and less than unity, which means that there is indeed cointegration. Again, the GDP per capita and GDP^2 per capita show evidence for the EKC, because the coefficient of the former is positive and of the latter negative. FDI has a negative impact on CO_2 emissions per capita, but in this model, the effect is stronger (-0.20) in comparison to the previous model (-0.03). Remarkable is that renewable energy consumption seems to have a positive influence on CO_2 emissions per capita, which is not in line with the previous results and the expectations described in Chapter 2. However, if you look at the short-run effect, the coefficient is negative, as expected. Also the variables that take into account the share of GDP from the industry and service sector show remarkable results. One would expect that the higher the share of industry, the more CO_2 emissions and that the service sector is less polluting, so this coefficient would be negative. However, looking at the outcomes in Table 11, the higher the share of the industry sector, the lower the emissions per capita and the higher the share of the service sector, the higher the emissions per capita. Lastly, trade has both in the long and short-run a significant effect on the amount of emissions. In the short run, more trade results in more emissions per capita, while in the long-run it will lower the amount of emissions per capita in a country. The latter can indicate that the technique effect will prevail, because more trade can diffuse cleaner and more efficient production techniques which can reduce the amount of CO_2 emissions. It takes time to implement new and cleaner techniques, which will explain the positive effect in the short-run and the negative effect in the long-run.

Table 11 Outcomes Model 4

Variables	**Pooled mean group**		**Mean group**	
	Long-run	Short-run	Long-run	Short-run
ECT		-0.20^{***} (0.00)		-0.88^{**} (0.01)
$\ln CO_{it-1}$		-0.13 (0.10)		0.20 (0.21)
$\ln GDP_{it}$	1.73^{***} (0.00)	-0.03 (0.99)	2.06 (0.77)	1.88 (0.63)
$\ln GDP2_{it}$	-0.09^{***} (0.00)	-0.01 (0.90)	-0.02 (0.97)	-0.18 (0.53)
$\ln FDI_{it}$	-0.20^{***} (0.00)	-0.03 (0.62)	0.35 (0.52)	0.07 (0.76)
$\ln REN_{it}$	0.14^{**} (0.03)	-0.43^{*} (0.05)	6.92 (0.26)	-0.26 (0.80)
$\ln FEN_{it}$	0.75^{***} (0.00)	0.58^{**} (0.03)	4.19 (0.12)	0.27 (0.74)
$\ln FEN_{it-1}$		0.16 (0.57)		-0.15 (0.71)
$\ln IND_{it}$	-0.14^{*} (0.09)	-0.19 (0.15)	0.07 (0.97)	-1.09 (0.16)
$\ln IND_{it-1}$		*0.05 (0.48)*		*-0.60 (0.07)*
$\ln SERV_{it}$	0.22^{***} (0.00)	-0.34 (0.26)	-4.06^{**} (0.04)	-0.95 (0.31)
$\ln TRADE_{it}$	-0.30^{***} (0.00)	0.15^{**} (0.01)	-0.25 (0.49)	-0.02 (0.88)
Constant		-1.96^{***} (0.00)		24.16 (0.32)
Hausman		0.35 (1.00)		

*The asterisks ***, ** and *, indicate a statistical significance at a 1, 5 and 10 percent level, respectively. The values between brackets ( ) denote the p-values.*

5.6. High- and low-income countries

The above analysis is done for a panel of 16 countries, with a wide range in the level of income between the countries. The conclusions, which are given above are therefore very general. As mentioned in Chapter 2, the effects of variables on the amount of CO_2 emissions depends sometimes on the 'phase' of the country. For example, if countries have a low income level, FDI will have a different impact than FDI in countries with a high income level. This refers to the pollution haven hypothesis, which is discussed elaborately in Chapter 2. This pollution haven hypothesis postulates that high-income countries reallocate their polluting production to low-income countries. Searching for evidence for this hypothesis is more difficult in an analysis as done in this chapter. That's because, in this analysis, we cannot distinguish between high and low-income countries. Also the other variables included in the analysis will show probably other results when we make a panel of high-income countries and low-income countries.

For this thesis, the panel of 16 countries was split up in two panels: the low- and medium-low income countries and the upper-medium and high-income countries. The next step was to carry out the analysis for these two new panels, with the corresponding unit root tests, cointegration test and the estimation of the four models. However, the results of the models were not as expected. For simplicity, we will call the panel with the low-income countries, panel B1 and the panel with high-income countries, panel B2. For the former, only Model 1 and model 3 showed consistent results. Panel B2 only showed 'normal' results for Model 2 and 4 (see Table 12). First of all, it is surprising that the two panels, both estimate 2 models in the right way, but not the same models. That is remarkable, but also raises the question of why not all the models can be estimated. Therefore, we will explain what went wrong in estimating model 2 and 4 in panel B1 and in estimating model 1 and 3 in panel B2.

Table 12 Overview, model estimation for two different panels

	Panel B1	Panel B2
Model 1	✓	*Problems Hausman test*
Model 2	×	✓
Model 3	✓	*ECT not significant*
Model 4	*Problems Hausman test*	✓

In Table 12, a clear overview is provided of the models that can be estimated and of the problems encountered by estimating the other models. No results can be obtained for Model 2 of panel B1. The remaining models can be estimated, but give uncommon results. The problem occurring in model 4 of panel B1 and model 1 of panel B2 is related to the Hausman test. The chi-square statistic is negative, which is not allowed in this test statistic. Therefore, the p-value for the Hausman test is not generated and it can not be determined which estimator is consistent and efficient. For model 3 of panel B2, the problem that occurs is that the Hausman test points to the PMG estimator as the most efficient estimator. However, the ECT is not significant, which means that there is no cointegration. We discussed in Chapter 4, that the general ARDL model can be applied in that case. However, the PMG estimator or MG estimator are not suitable for estimating a general ARDL model. Applying another estimator for this model is beyond the scope and time of this thesis. In conclusion, the results of the models for two separate panels give some problems for the Hausman test and also an explanation why Models 1 and 3 for panel B1 and Models 2 and 4 for panel B2, can be estimated without such problems is not clear. A solution, to distinguish between the 8 low- and 8 high-income countries is to include a dummy variable in the original analysis. Unfortunately, a dummy variable cannot be added when the model is estimated with the PMG and MG estimator in Stata.

It is difficult to give an explanation, why the models can be estimated for the panel of 16 countries, but not when we split up this panel into 8 countries per panel. The only explanation, which is obvious, would be that the estimator is developed for a large N and a large T (Blackburne and Frank 2007). By splitting up the original panel, maybe the number of countries is too small. However, when looking at Table 1 in Chapter 3, we see that Baek (2016) and Rafindadi et al. (2018) apply the PMG and MG on a panel with five and six countries, respectively. In conclusion, it is decided to omit the analysis for the 2 separate panels from this thesis.

5.7. Conclusion

This chapter shows the results of the econometric analysis. First, all the variables are tested for unit roots and all the variables are stationary in levels or first differences. Secondly, the optimal lag lengths for both the dependent and the independent variables are determined with the Akaike information criterion. Thereafter, the Pedroni test is carried out, to see if there is cointegration in the data. This test was carried out, because most of the variables are integrated with order one and a cointegration relationship can have an influence on the short-run dynamics of the model. The test shows ambiguous results and therefore an ECT is included in the model. This ECT ensures that consistent results are obtained if there is cointegration. Next to that, the ECT also indicates if cointegration is present in the data. The results of the cointegration tests are ambiguous, but the ECT shows clearly that there is a cointegration relationship in the data. Thereafter, four different models are estimated with the ARDL model including an ECT. The Hausman test is conducted to see which estimator, the PMG or MG, is consistent and efficient. For all the models, the PMG is the most efficient estimator. The most remarkable in this analysis is that the first model (with 5 independent variables) only shows one variable that has a statistically significant influence on the amount of CO_2 emissions per capita in the long run: the share of fossil fuel energy consumption of the total amount of energy consumption. The second model adds 2 more variables: the share of the industry sector and the service sector of GDP. This results in more variables that are significant in the long run. Now, not only fossil fuel energy consumption has a significant positive impact on the amount of CO_2 emissions per capita, also renewable energy consumption shows a significant negative impact, as expected. Also GDP per capita shows a significant positive influence on CO_2 emissions per capita, which means that an increase in GDP per capita results in an increase in the amount of emissions per capita (i.e. scale effect). The share of industry as a percentage of GDP is also significant and has a negative relationship with CO_2 emissions per capita. This is not as expected, because one would expect that the industry sector is polluting and therefore a higher share of industry would lead to an increase in the amount of emissions per capita. The third model includes all the variables of Model 1 and trade as the extra variable. Now all the variables have a significant influence in the long run. Again, renewable energy consumption and fossil fuel energy consumption show a negative and positive relationship, as expected. In this model also GDP^2 per capita is significant, as well as GDP per capita. Looking at these two variables, we can conclude that there is evidence for the EKC, because GDP per capita has a positive coefficient and GDP^2 per capita a negative coefficient. The other two variables, FDI and trade, show both a small influence on the amount of emissions per capita. FDI lowers the amount of emissions per capita and trade increases the amount of emissions per capita. The last model includes all the variables of Models 1, 2 and 3. It is not surprising that all the variables have a significant influence on the amount of CO_2 emissions per capita in the long run. The two variables, GDP per capita and GDP^2 per capita, show, as in the third model, that there is evidence for the existence of the EKC. As well as FDI, which still indicates that it lowers the amount of emissions per capita. This is also the case for trade in the long run, but in the short-run it increases the amount of emissions per capita. The share of the industry and the service sector, are in contradiction with the expectation, because there is a negative relationship between industry and CO_2 emissions per capita and a positive relationship between the service sector and CO_2 emissions per capita. Also the variable for renewable energy consumption shows a remarkable result. In de previous models, the coefficient of the variable was negative (as one would expect) and now the coefficient is positive. However, in the short run, the variable shows a negative relationship with CO_2 emissions per capita, which is again in line with the expectations. For this chapter, also an analysis is performed for two panels with lower-income countries and for higher-income countries. The estimations of the models, however, caused some problems. Mainly, an inconsistent statistical value for the Hausman test and an ECT which was not significant. Therefore it was decided to leave these analyses out.

6. Discussion

As pointed out in the introduction of this thesis report, this thesis is relevant in two aspects. First, in the existing literature, there is no clear answer on the influence of the variables, used in this thesis, on the amount of CO_2 emissions. Also the set of variables as used in this thesis, is as far as we know, not tested before. Next to filling the knowledge gap in the scientific literature, this thesis is also relevant in a social aspect. Nowadays, policymakers are focussed on reducing the amount of CO_2 emissions and the corresponding negative effects of greenhouse gasses. Therefore, it is important to know what factors influence the amount of emissions, so regulations can be adjusted in response to the findings of this thesis.

Next to the findings that answer the research question of this thesis directly, the most remarkable of the econometric analysis is that the significance of the variables, depends heavily on the number and/or composition of variables that are included in the model. We see that in the model with only five independent variables, only one has a significant influence on the amount of CO_2 emissions per capita, while the last model with eight independent variables shows that all variables have a significant influence.

The finding which is not surprising is that fossil fuel energy consumption increases the amount of CO_2 emissions per capita. Most other research (discussed in Chapter 3), only include total energy consumption as a variable, but Riti et al. (2017) and Rafiq et al. (2016) also test the influence of fossil fuel energy consumption and non-renewable energy consumption, respectively. These all indicate that (fossil fuel) energy consumption has a positive relationship with the amount of CO_2 emissions per capita, which is in line with the result of this thesis. The same two articles, also researched the influence of renewable energy consumption on the amount of emissions per capita, as did Mert and Bölük (2016). All three find a negative relationship between renewable energy consumption and CO_2 emissions per capita. This outcome was also found for Models 2 and 3 of this thesis. However, Model 4 shows a significant positive relationship with the amount of emissions per capita in the long-run and a significant negative relationship in de short-run. That is not in line with the other articles and the result of the other two models. The variables for GDP per capita and the GDP^2 per capita, are in line with the environmental Kuznets curve as described in Chapter 2. The EKC postulates an inverted-U shaped curve for the relationship between GDP per capita and CO_2 emissions per capita. That would imply that the GDP variable should have a positive relationship with the amount of emissions, also called the scale effect, and the GDP^2 variable should have a negative relationship. The results of the analysis are in line with this theory, because GDP per capita shows a significant positive relationship in Models 2, 3 and 4 and GDP^2 per capita a significant negative relationship in Models 3 and 4. That GDP per capita increases the amount of CO_2 emissions per capita, is often confirmed by other research (Riti et al. 2017; Omri 2013; You et al. 2015; Tang and Tan 2015; Rafiq et al. 2016; Baek 2016). However, the existence of the EKC is ambiguous. The findings of this thesis are in line with Baek (2016), You et al. (2015), Tang and Tan (2015), Pao and Tsai (2011) and Boutabba (2014), because they find evidence for the EKC. However, other articles do not find evidence for the EKC (Chandran and Tang 2013; Zhu et al. 2016; Mert and Bölük 2016). Another important relationship in this research is the amount of FDI inflow in a country and the influence on the amount of CO_2 emissions per capita. This variable has also evidence for both negative and positive relationships with CO_2 emissions per capita. Not only when looking at the outcomes of other research, but also in the theory. The pollution haven hypothesis, predicts a positive relationship and the pollution halo hypothesis a negative relationship. The analysis of this thesis confirms the pollution halo hypothesis, because the coefficient of the FDI variable is significantly negative for Models 3 and 4. The share of the industry and service sector in a country reflects the composition effect. This effect postulates that the industry sector is associated with an increase in CO_2 emissions per capita and the service sector with a decrease in CO_2 emissions per capita. This is also confirmed by other research, which carried out an analysis with these variables (You et al. 2015; Zhu et al. 2016; Rafiq et al. 2016). The results of the analysis in this thesis are therefore unexpected. The variable for the share of industry has a negative coefficient, which means that an increase in the share of industry, results in a decrease in the amount of emissions per capita. The share of the service sector has a positive coefficient, which means that an increase in the share of the service sector will lead to an increase in the amount of emissions per capita. This is remarkable, because it is not in line with both the theory and the outcomes of other research. The last variable, trade, shows ambiguous results. In Model 3 the variable shows a positive relationship and in Model 4 a negative relationship. Looking at other articles, Zhu et al. (2016) and Rafiq et al. (2016), find a negative relationship between trade and CO_2 emissions per capita, which is in line with Model 4. Boutabba (2014), however, took this variable also into account, but found no significant influence of this variable on the amount of emissions.

The analysis carried out for this thesis has also some limitations. The choice for panel data has some advantages, but at the same time rules out the advantages of a time series analysis. The country-specific intercept captures some characteristics of the individual countries. However, the long-run relationships between CO_2 emissions and the variables, are assumed to be homogeneous. Therefore, the conclusions drawn in this thesis are very general and the influence of the variables can differ among countries. That was already clear in Chapter 2, where the influence of FDI and GDP on the amount of emissions were described by theories and depend on how developed a country is. The environmental Kuznets curve postulates, that GDP per capita will increase the amount of emissions per capita in low-income countries, but will decrease the amount in high-income countries. Also the pollution haven- and halo hypothesis, focus especially on the influence of FDI on developing countries. Therefore, these theories can be tested much better in a time series analysis or a panel with only developed or developing countries. As described in Chapter 5, the panel of 16 countries was split up in the high-income countries and low-income countries, to especially test these theories and see if there was a difference in the influence of the variables on the amount of CO_2 emissions. Unfortunately, the results were omitted from this thesis, because we couldn't explain the somewhat strange results. What should be kept in mind is therefore that the conclusions drawn, about the influence of the different variables, are very general and can be different for every individual country. There can also be a bias in the results, as a result of the countries chosen for the panel. The panel has a range in different income levels and geographical distribution. However, one could wonder if the fact that these countries have available data from 1990 till 2014, says something about the particular characteristics of these countries (e.g. institutional quality). Another limitation of this research is that only uni-directional relationships are estimated (i.e. only one dependent variable). While in Chapter 2, it is discussed that the variables mutually influence each other as well and that the relationships between the variables can also work both ways. Also, the estimation of the ARDL model with the (P)MG estimator seems to be very sensitive to the model specification. Just looking at the different models and the fact that for the model with five independent variables, only one variable is significant and that the model with eight independent variables result in eight significant variables. Besides that, in the process towards these four models, we came across that the number of lags that are included, also influences both the significance as well as the sign of the coefficients. This is very important to keep in mind, because the model specification, therefore, influences the outcomes of the models fairly. Lastly, in Chapter 3, diagnostic tests are shorty discussed, because some other articles applied diagnostic tests after their model estimation. This is done for different purposes, like testing if residuals are normallly distributed or see if the coefficients are stable (do not contain structural breaks). In this thesis, however, such tests are not carried out and therefore some potential problems can not be detected.

7. Conclusion

All the chapters of this thesis report contribute to answering the following research question: *To what extent do FDI, income and energy consumption affect the amount of CO_2 emissions?* In this concluding chapter, therefore, the conclusions and main findings of every chapter are discussed, as well as recommendations for further research

First, a literature review is conducted, whereby the most important concepts and theories among the four variables, CO_2 emissions, FDI, GDP and energy consumption, are formulated and explained. Starting with the environmental Kuznets curve, which postulates that in countries with low incomes, when GDP per capita increases, also CO_2 emissions per capita will increase. This is called the scale effect. However, when countries become richer, they develop better and cleaner technologies (i.e. technique effect) and shift from an agricultural economy to an industrial economy and in the end to a service economy (i.e. composition effect), resulting in a decrease in CO_2 emissions per capita. Two other theories explain the relationship between FDI and CO_2 emission: the pollution haven hypothesis and the pollution halo hypothesis. The former postulates that FDI flows from developed to developing countries, because developing countries have a comparative advantage for polluting production. This is the result of their weak environmental regulations and therefore FDI inflow is associated with an increase in polluting production and thereby an increase in CO_2 emissions. The pollution halo hypothesis, however, postulates that the inflow of FDI is associated with a decrease in CO_2 emissions, because cleaner and more efficient production techniques will be spread in the country. The last variable, energy consumption, is often associated with an increase in CO_2 emissions. Only when the energy source is less polluting, CO_2 emissions can be reduced. Lastly, a couple of other variables also seem to be relevant, when investigating the drivers of CO_2 emissions. A couple will be included in this analysis as well: the percentage of GDP generated by the industry sector, the percentage of GDP generated by the service sector and the amount of trade in a country as a percentage of GDP. The former two, represent the composition effect. The variable representing the amount of trade is often included in other research, to avoid omitted variable bias.

Investigating the influence of the above-mentioned variables is very relevant. Not only because there is no consistency in the literature about the role of the variables in the amount of CO_2 that is emitted, but also because policymakers try to set policies to reduce emissions. Therefore a better view of these relationships is relevant for both scientific and policy purposes. To estimate these relationships, first a suitable method should be found. The method is determined based on the methodology review in Chapter 3. It seems that both the vector error correction model (VECM) and the autoregressive distributed lag (ARDL) model, are the most suitable models. They are both dynamic models (i.e. include lags) and they can estimate both short- and long-run effects at the same time. However, the VECM, has a vector of dependent variables, while the ARDL model only has one dependent variable. Considering the research question of this thesis, the ARDL model is a more appropriate choice, because the focus is on CO_2 emissions as the dependent variable. The ARDL model also has the advantage that the model can be estimated with variables that are I(0), I(1) or both. Also when cointegration exists, the model can be converted to an ARDL model with an error correction term (ECT), so cointegration will not cause problems in the model estimation. Other articles, which used the ARDL model, applied most times the pooled mean group (PMG) and mean group (MG) estimator, to estimate their model. Before the model can be estimated, unit roots should be tested, optimal lag lengths should be determined and cointegration tests should be applied. The methodology review and the options available by Stata (the software used to carry out the analysis), determined which tests were used for this analysis. The unit roots were tested by five different unit root tests, the lag length determined with the Akaike information criterion and the Pedroni cointegration test is applied.

The analysis is performed for a panel of 16 countries, with a broad range in different income levels and geographical distribution. The time period over which the analysis is performed is determined by the availability of the data and is from 1990 till 2014. The variables are in natural logarithms, because the relative changes instead of absolute changes will be obtained from the estimation and heteroskedasticity will be reduced. In total four models are estimated. The first one with only the most important variables, CO_2 emissions, FDI, GDP, GDP^2, fossil fuel energy consumption and renewable energy consumption. The squared GDP variable is included to test the EKC, which postulates an inverted-U shape relationship between GDP and CO_2 emissions. Also energy consumption is split up in two different sources, because it is likely that there will be a difference in the (strength of) influence on the amount of emissions. The second and third model, will add the share of industry and the service sector (Model 2) and the amount of trade (Model 3), on top of the variables included in Model 1. The last model includes all variables. The models are estimated with the PMG and MG estimator, where after the Hausman test indicates which estimator is the most efficient.

The results of the unit root tests show that FDI is stationary in levels (i.e. I(0)) and that the other variables show either ambiguous results or clear that the data is stationary when first differences are taken (i.e. I(1)). However, all variables are stationary in first differences or in levels, whereby the ARDL model can be applied. The Pedroni cointegration test shows ambiguous results as well and therefore an ECT is included to, on the one hand, adjust for cointegration and on the other hand, see if this term indicates a cointegration relationship. In all four models, the ECT proves that cointegration exist and therefore all four models include an ECT. The Hausman test, applied after all the models, indicate that the PMG estimator is the most efficient estimator and therefore the results of this estimator are discussed.

The most remarkable, if you look at the four models, is that in the first model, only one variable has a significant influence on the amount of CO_2 emissions per capita and in the last model, all variables show a significant influence. Overall there seems to be evidence for the EKC, because out of the four models, in three models GDP per capita has a positive relationship with CO_2 emissions per capita and the squared-GDP per capita variable is significantly negative in two of the models. This is in line with the predictions of the environmental Kuznets curve. FDI has no significant influence in the first two models, but in the last two models, the variable has a significant negative influence. Which means that more FDI, lowers the amount of CO_2 emissions per capita in the long run. The only variable that is significant in all the four models, both in the long- and short-run, is fossil fuel energy consumption. As expected, fossil fuel energy consumption increases the amount of CO_2 emissions per capita. Renewable energy consumption becomes significant when additional variables are included on top of the basic model. In Model 2 and 3, the consumption of renewable energy lowers the amount of emissions per capita. However, in the fourth model (with all the variables), the coefficient is positive in the long-run and again negative in the short-run, which is remable. The share of industry has a negative relationship with CO_2 emissions per capita (i.e. lowers the amount of emissions), while the share of service has a negative relationship with CO_2 emissions per capita (only significant in the last model), which is not in line with the composition effect. The trade variable shows ambiguous results, because in Model 3, this variable has a positive relationship with CO_2 emissions per capita and in Model 4 a negative relationship. In the latter model, however, the variable has a positive relationship in the short run.

The research question of this thesis has no straight answer, because the results are often ambiguous and depend on the model specification. It is however clear that fossil fuel energy consumption and GDP per capita will increase the amount of emissions per capita. There is also evidence for the environmental Kuznets curve, in the models were the trade variable is included as well. FDI lowers the amount of emissions per capita and the amount of energy consumption from renewable energy shows predominantly a negative influence as well.

This research is a solid basis for further research. As mentioned in the discussion chapter, there are some limitation and a couple of them can be solved in further research. As mentioned in Chapter 3, the VECM model also seems to be a good model to estimate these relationships, therefore this research can also be carried out with a VECM model. This model has more independent variables and therefore the relationships among the variables can be researched as well. Also the original panel can be extended (for both a VECM and ARDL model), where after the panel can be split up in high- and low-income countries. This would give a better view of the influence of the variables in developed and developing countries and the theories, as described in Chapter 2, can be better linked to the results.

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