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# Money and the Air

*The Impact of Income, Preferences, and Regulation on Particulate Matter Pollution*

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# Abstract

In this thesis we investigate the impact of preferences, income and regulation on $PM_{2.5}$ levels. The thesis uses a combined data set of income, population weighted concentration levels of $PM_{2.5}$ for 157 countries from 1990 to 2017. Using a fixed effects model, we find evidence for an inverted U-shaped relationship between income and pollution, supporting the hypothesis of an Environmental Kuznet Curve for $PM_{2.5}$. Furthermore, the curve has changed in recent time and pollution is more sensitive to income in from 2011 to 2017 than for the period as a whole. The estimated turning points are \$6,015 for the full period and \$2,860 for 2011-2017. Income is not found to have different effects on $PM_{2.5}$ pollution in developed and developing countries.

Assuming preferences to be constant, we find relationships between patience, negative reciprocity, risk taking and $PM_{2.5}$ pollution.
Greater levels of patience are seen with lower levels of estimated time invariant $PM_{2.5}$ pollution, while higher levels of negative reciprocity and risk taking are seen with lower levels of $PM_{2.5}$. Negative reciprocity also seems to have an effect on the relationship between income and pollution. Countries with higher levels of negative reciprocity have a different estimated EKC and reaches the turning point faster (\$4,620) than countries with lower levels (\$12,094).

Though the results indicate preferences and income to have effects on $PM_{2.5}$ pollution, the analysis does not propose causality. Using a difference-in-difference approach, we analyse how regulations and policy can have an effect through the EU' Directive 50/2008. The isolated effect of the directive is estimated to be a reduction in $PM_{2.5}$ levels of 6 %. This effect is robust to inclusions of EKC-relationships in the estimation.

# Preface

We would like to thank our supervisor Krisztina Molnar for providing invaluable help, assistance and guidance. We especially appreciated her taking so much of her time to guide two clueless master students. Krisztina showed great interest in our work from day one, which was a great motivation for us. Finally we would like to thank her for being available even at short notice. For other master's students we cannot recommend Krisztina enough.

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# 1. Introduction

Every year 3.1 million people die as a result of fine particulate matter ($PM_{2.5}$) pollution (WHO, 2013). Both the EU and the WHO has deemed that there is no safe level of exposure for $PM_{2.5}$ (EU, 2008) (WHO, 2003). $PM_{2.5}$ pollution is present in all over the world. In Bergen, the home city of NHH, $PM_{2.5}$ pollution during winter is often so bad asthmatics and people with respiratory disease have to stay indoors (Høisaker, Sundvor, Johnsrud, Haug, & Solli, 2017). On both a micro level and a macro level $PM_{2.5}$ pollution causes great societal harm. Therefore understanding the relationship between $PM_{2.5}$ and economic growth can help decision makers enact polices to combat $PM_{2.5}$ pollution. Economic growth is often associated with environmental degradation. Several economists have challenged this view. They argue that though economic growth may initially have a negative effect on the environment, as a country grows richer this relationship will reverse itself, and environmental quality will improve. This hypothesis is known as The Environmental Kuznets Curve (EKC) and postulates an inverse U-shaped relationship between economic growth and environmental degradation.

In this thesis we investigate relationships between $PM_{2.5}$ pollution, income, preferences and regulatory action.

First, we will estimate the relation between $PM_{2.5}$ pollution and income using a panel of 157 countries observed from 1990-2017. Our main hypothesis is that this relationship has an inverted U-shape. This means that we can estimate a turning point for $PM_{2.5}$ pollution where pollution levels start to decline with income growth. We will also investigate if the EKC is the same for the entire world and if the shape of the EKC has changed over time.

Using a new data set on economic preferences we explore the possible links between patience, risk taking, altruism, trust, negative and positive reciprocity and $PM_{2.5}$ pollution. We investigate the possibility of preferences affecting both time invariant levels and income effects on pollution.

Finally we will use the implementation of EUs' Directive 50 to show how regulatory action can impact particulate matter levels. The EUs' implementation of Directive 50 covers all EU-countries. This gives us a large sample of countries which makes inference clearer. To estimate the effect of the Directive we use difference-in-difference estimation. We use both developed and developing countries as control for the effect of Directive 50.

# 2. Background

## 2.1 Particulate matter

Particulate air pollution is a measure of the number of particulates suspended in the air measured in µg per $m^3$. The particulates can be either solid or liquid and are characterized by their aerodynamic size measured in micrometres. Commonly suspended particulate matter is separated into two categories: particulates between 10µm and 2.5 µm are referred to as $PM_{10}$ and particulates that are smaller than 2.5µm are referred to as $PM_{2.5}$. The particulates can be either organic or inorganic. This type of air pollution can come for both natural and manmade sources. Some natural sources for $PM_{2.5}$ are windblown dust, sea salt, pollen and spores. Manmade $PM_{2.5}$ can form as a by-product of combustion such as smoke, soot or fumes. The emission from industrial activity contributes both directly to PM-pollution and indirectly as the combustion by-products can react in the atmosphere breaking down into or forming other harmful particulates (WHO, 2003).

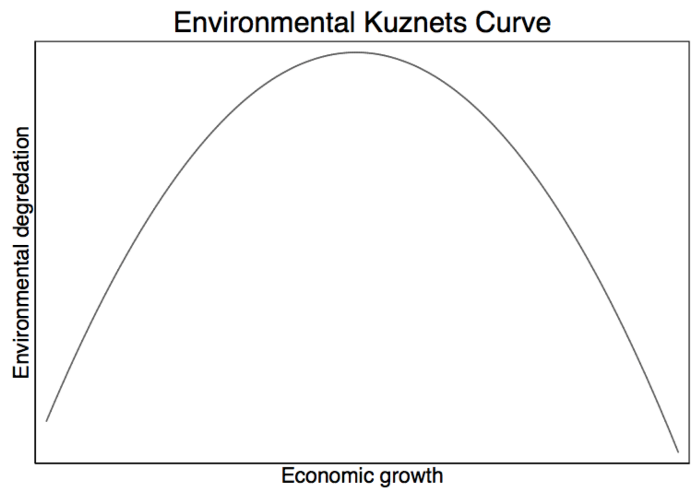
$PM_{2.5}$ is generally considered to be more dangerous than $PM_{10}$ as the particulates are smaller can enter deeper into the body (WHO, 2003). The main mechanism in which $PM_{2.5}$ enters the body is by inhalation. The particulates are too small to be filtered out by the respiratory system and enters the cardiovascular system through the lounges and transferring potentially harmful molecules into the bloodstream (WHO, 2003).

$PM_{2.5}$ exposure have both short and long-term harmful effects and it is estimated that 3,1 million people die as a result of $PM_{2.5}$ pollution every year (WHO, 2013). Studies have shown that elevated $PM_{2.5}$ concentrations can impact test scores (Roth, Air pollution, educational achievements, and human capital formation, 2017) and increase crime in a given area on days with increased $PM_{2.5}$ concentration (Roth, Bondy, & Sager, Crime is in the Air: The Contemporaneous Relationship between Air Pollution and Crime, 2018). There are also serious long-term health effects. Studies have shown that long term exposure to $PM_{2.5}$ causes build-up of harmful nanoparticles in the brain increasing the risk of a range of cognitive diseases such as Alzheimer’s as well as impeding brain function (Maher, et al., 2016). In addition to this, exposure to $PM_{2.5}$ is linked to an increased risk of a range of cancers (Weinmayr et al, 2018).

## 2.2 Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) is a hypothesised relationship between environmental degradation and economic growth. The EKC-hypothesis is that environmental degradation initially increases with economic growth, before it at some level of economic development reaches a turning point and decreases with further economic growth. Thus, the hypothesised relationship takes an inverted U-shaped form. The existence of this hypothesised relationship is typically tested empirically by modelling the chosen indicator of environmental degradation as a quadratic function of GDP per capita. The EKC is named after Simon S. Kuznets who hypothesized that inequality in income distribution first increases with economic growth, before it reaches a point where further economic growth leads to lower income inequality (Kuznets, 1955).

Figure I




The figure illustrates the EKC concept.

The EKC concept was first introduced in Grossman and Krueger (1991). The study which looks at the environmental impacts of a North American Free Trade Agreement. The interpretation of environmental degradation is broad, but the main pillars in the literature are for concentrations and emissions of air, soil and groundwater pollutants. Some pollutants are naturally more appropriate to be measured in concentration levels, such as $PM_{2.5}$, while others are more precisely captured by emission levels, such as $CO_2$.

In a background study for the World Banks's 1992 World Development Report, Shafik and Bandyopadhyay (1992) state that in a complicated relationship between environmental degradation and economic growth, income has the most consistently significant effect on all indicators of environmental degradation. The study claims that economic growth could solve some environmental problems, but stresses that "there is nothing automatic about it", and that to reduce degradation, policies and investments need to be in place.

The findings of Shafik and Bandyopadhyay (1992) were included in the World Development Report (1992). Studying the relationship between economic development and the environment, the report reads "the view that greater economic activity inevitably hurts the environment is based on static assumptions about technology, tastes and environmental investments" (World Bank, 1992, p.38). The report suggests four important drivers for sustainable development; structure (the goods and services produced), efficiency (input per unit of output), substitution (ability to move away from scarce resources) and clean technologies and management practice (environmental damage per unit of input or output). Furthermore, the report reads "as income rise, the demand for improvements in environmental quality will increase" (World Bank, 1992, p.39) and "without incentives to use scarce resources sparingly, the pressure to reduce environmental damage will be weaker" (World Bank, 1992, p.39) imposing greater demand for environmental quality and greater pressure for sustainable growth in more developed countries with higher levels of income.

## 2.3 Effects of EU law

Shafik and Bandyopadhyay (1992) suggest that policies and investments need to be in place for economic growth to solve environmental problems, and that there is nothing automatic about the EKC. Economic growth does not decrease pollution per se but works through underlying mechanisms. In light of this we want to analyse the effects of such a policy – the EU directive from 2008 on ambient air quality Directive 2008/50/EC.

The directive defines and establishes new objectives for $PM_{2.5}$ including an upper and a lower threshold for annual average exposure to the population (EU, 2008). These thresholds are 17 $\mu g/m^3$ and 12 $\mu g/m^3$, respectively. 20 out of the 28 EU member states are represented in our dataset. In addition, we have chosen to include Norway as EEA-members are also obliged to follow. In 2005, three years prior to the directive, 11 of these countries exceeded the lower threshold and 5 exceeded the upper threshold[1]. In 2017 these numbers were decreased to 7 countries exceeding the lower and only Poland exceeding the upper threshold. Furthermore, the average annual $PM_{2.5}$ exposure in the 20 represented member states decreased from 14.6 $\mu g/m^3$ to 12.1 $\mu g/m^3$ in the same period.

## 2.4 Preferences

In the last decade, behavioural economics has gained increased attention and has had great impact in the field of economics. As a result, more data on economic preferences and behavioural characteristics has been made available. A lot of theories in environmental economics incorporate preferences as part of models, but little empirical work which include actual data on these preferences has been done. In this thesis, we try to bring a new perspective on the relationship between economic growth and environment by including such data.

[1] Statistics based on data set used in this thesis. $PM_{2.5}$ data from IHME.

# 3. Literature Review

There have been many studies over the years that have attempted to ascertain the relationship between pollution and economic development. Grossman & Krueger (1991) apply a Kuznets curve to study the relationship between a range of pollutants and economic development in an effort to assess the environmental impact of the implementation of NAFTA. Using data from a cross-section of urban areas in 42 countries, they investigate the relationship between concentrations of sulphur dioxide, particulate matter and dark matter, and per capita GDP. As there are different natural sources of these pollutants, they include a vector of explanatory variables including dummies to indicate whether the monitoring station is located near the coast, a desert, in a central city, an industrial or residential area. They find evidence for the inverted U-shaped relationship for sulphur dioxide and dark matter and turning points for both around $8,000. Shafik and Bandyopadhyay (1992) also find evidence of the inverted U-shaped relationship for various environmental indicators, including ambient levels of particulate matter.

A number of papers have used the concept of an EKC to tackle a range of phenomena from deforestation (Koopa & Tole, 1999) to water usage (Durate, Pinilla, & Serrano, 2013). The most common way to apply the EKC is estimating the relationship between income and different pollutants. Grossman & Krueger (1995) builds on their previous work to investigate if there is an EKC-relationship between income and urban air pollution and a range of water pollutants finding turning points around $8000. In Selden & Daqing (1994) they estimate an EKC relationship for suspended particulate matter (as well as for NO2, SOX and CO) using cross-sectional data for a range of countries finding turning points around $9,500 in 1985 dollars. Shafik (1994) finds an EKC-relation using a cross-sectional data for a range of pollutants including suspended particulate matter.

There has been relatively little research specifically concerning $PM_{2.5}$ and economic development using cross-country data when compared to other air pollutants. However there have been some studies using data on city or county level to investigate if there is an EKC for $PM_{2.5}$. Brajer, W.Mead, & Xiao (2011) find in their study using a cross-section of 139 Chinese cities between 1990-2006 that there seems to be a significant EKC relationship between particulate matter and income. They estimate a turning point of 3784RMB (about $550) and 6253 RMB (about $900) when controlling for population. Haoab & Liuab (2015) find turning points ranging from 9000RMB (about $1300) to 40000RMB (about $5700) using a cross-section of 73 cities from 2013. Using a cross-sectional dataset of US county data from 2000 Keene & Deller (2015) find an EKC relation and estimate turning points for $PM_{2.5}$ pollution ranging between $24000-25000.

Over the years a number of articles criticizing the EKC-hypothesis have been published. Stern (2004) claims that the EKC-hypothesis is incorrect both due to it not being econometrically robust and because of developing countries adopting new technology earlier than developed countries. Several studies other have critiquing the EKC hypothesis for not being robust for a range of pollutants (Vollebergh, Melenberg, & Dijkgraaf, 2008) (Wagner, 2008). Stern & Dijk (2017) uses a dataset of 151 countries and observations of $PM_{2.5}$ in 1990, 2000 and 2010. The authors claim that, using a convergence model, they cannot find a statistically significant turning point for $PM_{2.5}$ pollution.

There have also been articles trying to establish a more stylised model. Pecchenino (1994) sets up an overlapping generations model that analyses the relationship between economic growth and the environment where individuals make decisions about consumption and environmental abatement. Nakagawa, Sato, & Yamaguchi (2014) show in an OLG model with changes in abatement technology how improvements in technology in one country can improve the environment for both.

This is a review of some of the literature on the EKC with regards to the most relevant articles for our purposes. The literature on EKC is vast and too large to be extensively covered in this thesis. However, we believe that in the section we have provided a brief overview of the most relevant parts of the literature. In general the most common approach to model $PM_{2.5}$ and economic development is by using cross-sectional data to estimate a cubic relationship, but some authors have put forward strong econometric critiques of this claiming that this method is not sufficiently robust.

One thing many EKC studies do is to compare their estimated turning points to the turning points in the literature. This is difficult to do as there has been one other study looking $PM_{2.5}$ on a country level and this study fails to estimate a significant turning point (Stern & Dijk, Economic growth and global particulate pollution concentrations, 2017). We cannot use the turning points from the studies using cross-sectional data from one country as the estimated turning point is for that country specifically. Our turning points are either global or estimated for developed or developing countries.

There is also a range of literature exploring effects of different environmental regulations. In a widely recognized paper Chay and Greenstone (1998) estimates the cost and benefits of The Clean Air Act regulations in the American housing market. Focusing on total suspended particulates (TSP), one of their results is that TSP decreased significantly more in ‘nonattainment’ counties – counties which had levels of TSP exceeding the federal ceiling at the time of the implementation.

Greenstone (2003) investigates the effect of the same regulations for a broader set of pollutants, including particulate matter, in the American iron and steel industry. Controlling for the possibility that factories move emissions from air to water, the paper finds evidence that total emissions per unit of output declined in ´nonattainment´ counties.

Bennear (2007) evaluates the effect of management-based regulations for toxic chemical controls during the 1990s in American manufacturing. Management-based regulations do not set given goals or measures but, require regulated entities to evaluate their production processes and set goals themselves. Using a difference-in-difference approach, the paper finds that management-based regulations had a negative effect on regulated manufacturing plants releases of toxic chemicals.

# 4. Data

We need a range of different data to conduct the three parts of our analysis. Firstly, the Environmental Kuznets Curve estimation requires data on $PM_{2.5}$ pollution for a broad set of countries over time. Secondly, we a comparable measure of the respective countries' GDP per capita. Thirdly, we need to establish a measure for the socio-economic development in order to investigate if the estimated EKC differs for developed and developing countries. Fourthly, we need to obtain data on economic preferences. Descriptive statistics of the gathered data is presented in 4.2. We have decided to present these without further comments.

## 4.1 Data collection

### 4.1.1 Environmental Kuznets Curve data collection

We use a data set on particulate matter concentrations from the (IHME, 2018), which is a collaboration between Health Effects Institute and the Institute for Health Metrics and Evaluation. It includes population-weighted concentrations of ambient $PM_{2.5}$ pollution in 195 countries every fifth year between 1990 and 2010, and every year from 2010 to 2017. To estimate the concentrations of fine particulate matter, the contributors combine data from air pollution monitoring stations, satellite observations and global chemical transport models. Concentration levels are reported as population-weighted annual means.

We use a socio-demographic index (SDI) from the same report (IHME, 2018) in our further analysis to distinguish between developed and developing countries. It includes both an annual socio-demographic score for each country and a classification using the 2015 scores. Countries are classified as low, low-middle, middle, high-middle or high SDI countries. There are some countries for which we have SDI scores, that the classification is missing[2]. This includes countries such as Brazil, China, India, Japan, Kenya, Mexico, Saudi Arabia, South Africa, Sweden, the United States and the United Kingdom. To classify these countries, we have made thresholds to be the minimum SDI value within each classification level, using the socio-demographic scores of 2015. Different countries have experienced different socio-

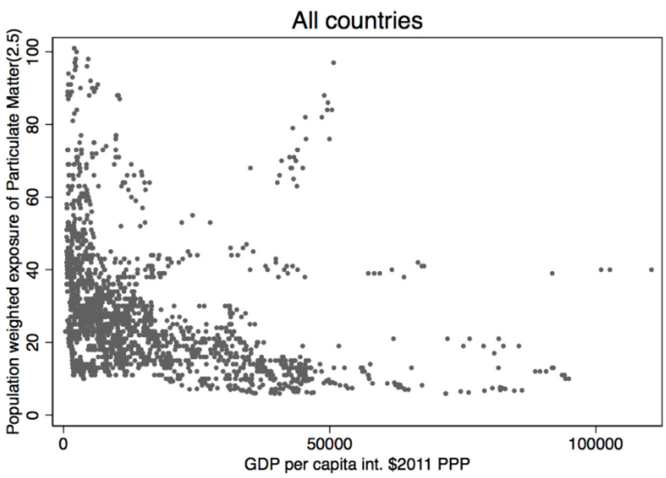
[2] For some countries in the IHME data SDI classification is split into regions and cities, and thus miss classification on an aggregated level.

demographic development from 1990, and thus some countries would have been classified differently in previous years. The benefit of using a static classification is that when we want to distinguish between developed and developing countries, all data observations of one country is within the same classification group. Thus, rather than classifying each observation, we classify each country and hold this constant for all observations of the given country.

We use gross domestic product per capita from the World Bank International Comparison Program database (The World Bank, 2019). GDP data is measured in constant 2011 international dollars. An international dollar has the same purchasing power over GDP as the US dollar has in the United States.

When analyzing the hypothesized EKC relationship we make use of data of all countries that have a full set of particulate matter and GDP per capita data in the years 1990, 1995, 2000, 2005 and 2010-2017. Typically, some countries in the particulate matter data set miss data points on GDP as they were declared independent states at a later stage in time. Thus, we have a sample of 157 countries covering 96% of the world population in 1990. See Appendix A-5 for the list of countries. Our complete dataset of 1884 observations is presented in the following figure:

Figure II

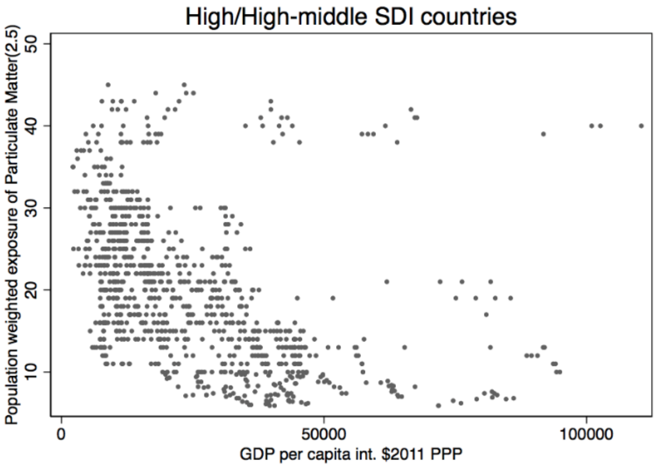



The figure plots $PM_{2.5}$ pollution against GDP/P for all 157 countries in the data set.
Correlation ($PM_{2.5}$, GDP/P) = -0.3177

From Figure II it seems hard to identify a clear pattern between $PM_{2.5}$ exposure and GDP per capita based on eyeballing econometrics. However, we remark that there seem to be fewer observations of high $PM_{2.5}$ exposure for countries with higher income. Thus, there might be a weak tendency of $PM_{2.5}$ concentrations decreasing with economic development.

The pattern appears clearer when analyzing a sub sample of 77 more developed countries, classified as high and high-middle SDI countries. In our sub sample of more developed countries, the negative relationship between $PM_{2.5}$ concentration and GDP per capita seems to be clearer.

Figure III




The figure plots $PM_{2.5}$ pollution against GDP/P for all high and high-middle SDI countries. Because of extraordinary levels of $PM_{2.5}$, Bahrain and Saudi-Arabia are excluded from the sub sample of visual reasons. Correlation ($PM_{2.5}$, GDP/P) = -0.1744

For both the full sample and the sub sample of more developed countries, we see the same patterns in the sub periods 1990-2005 and 2010-2017. We might believe there is a need for a certain level of socio-demographic development to be in place for a negative relationship between $PM_{2.5}$ concentration and GDP per capita to exist. The relatively lower correlation between income and pollution for developed countries might indicate that the relationship exists also for low income countries.

### 4.1.2 Preference data

From Falke et. al. (2018) we obtain data on six measures of economic preferences for 66 of the countries in our dataset. Through the Global Preference Study, Falke et. al. has collected data on levels of patience, negative and positive reciprocity, willingness to take risk, altruism and trust for 80 000 individuals across 76 countries. We make use of the aggregated data. The data is constructed as weighted scores of different survey items for each preference measure (Falke et.al., 2015). Brief explanations of the six preference measures are given in table I. An overview of the survey items from Falke et.al. (2018) is reported in Table B-I, appendix B.

| **Preference** | **Definition** |
|---|---|
| Patience | Willingness to give up something good today to receive more of it tomorrow. |
| Risk taking | Willingness to risk something good to potentially receive more of it. |
| Positive reciprocity | Propensity to return a favour, or show gratefulness materially after receiving a favour. |
| Negative reciprocity | Propensity to take revenge if you think you or someone else is treated unfairly. |
| Altruism | Willingness to give to a good cause without getting anything in return. |
| Trust | Belief in only good intentions of other people. |

Table I describes the preference measures from Falk et. al (2018).

## 4.2 Descriptive statistics

Table II

| 1990 - 2017 *(T = 12)* | Observations | Mean | Standard error | Min | Max |
|---|---|---|---|---|---|
| | | **World** *N* = 157 | | | |
| $PM_{2.5}$ | 1,884 | 28.41 | 17.29 | 5.9 | 101 |
| GDP/P | 1,884 | 15,495 | 17,267 | 373 | 110,433 |
| ln $PM_{2.5}$ | 1,844 | 3.18 | 0.58 | 1.78 | 4.62 |
| ln GDP/P | 1,844 | 9.02 | 1.20 | 5.92 | 11.61 |

| 1990 - 2017 *(T = 12)* | Observations | Mean | Standard error | Min | Max |
|---|---|---|---|---|---|
| | | **Higher SDI** *N* = 79 (77) | | | |
| $PM_{2.5}$ | 948 (924) | 21.57 (20.19) | 12.50 (9.12) | 5.9 (5.9) | 97 (45) |
| GDP/P | 948 (924) | 26,047 (25,562) | 18,583 (18,564) | 2,173 (2,173) | 110,433 (110,433) |
| ln $PM_{2.5}$ | 948 (924) | 2.93 (2.90) | 0.52 (0.48) | 1.77 (1.77) | 4.57 (3.81) |
| ln GDP/P | 948 (923) | 9.92 (9.90) | 0.73 (0.73) | 7.68 (7.68) | 11.61 (11.61) |
| **SDI** | | | | | |
| High SDI = 1 *(N=32)* | 384 (384) | 1 (1) | 0 (0) | 0 (0) | 1 (1) |
| High-middle SDI =1 *(N = 47) / (N = 45)* | 564 (540) | 1 (1) | 0 (0) | 0 (0) | 1 (1) |

| 1990 - 2017 *(T = 12)* | Observations | Mean | Standard error | Min | Max |
|---|---|---|---|---|---|
| | | **Lower SDI** *N* = 77 | | | |
| $PM_{2.5}$ | 924 | 35.56 | 18.68 | 10 | 101 |
| GDP/P | 924 | 4,584 | 4,433 | 373 | 35,632 |
| ln $PM_{2.5}$ | 924 | 3.44 | 0.51 | 2.30 | 4.62 |
| ln GDP/P | 924 | 8.08 | 0.82 | 5.92 | 10.48 |
| **SDI** | | | | | |
| Middle SDI = 1 *(N = 27)* | 324 | 1 | 0 | 0 | 1 |
| Low-middle SDI =1 *(N = 27)* | 324 | 1 | 0 | 0 | 1 |
| Low SDI = 1 *(N = 23)* | 276 | 1 | 0 | 0 | 1 |

Table II describes the data used in the EKC estimations. *N* notes the number of countries and *T* number of time periods in years. Number in parentheses for statistics of Higher SDI countries are statistics for the group excluded Bahrain and Saudi-Arabia. We miss SDI data for Russia in our World sample, thus the two sub samples add up to *N* = 156. Data is retrieved from The State of Global Air website, HEI, and World Bank.

| 2012 (*T = 1*) | Observations | Mean | Standard error | Min | Max |
|---|---|---|---|---|---|
| | Table III **World** *N* = 66 | | | | |
| Patience | 66 | 0.0157 | 0.3885 | -0.6152 | 1.0701 |
| ***(**Low < 0)* | *37* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *29* | *1* | *0* | *0* | *1* |
| Positive reciprocity | 66 | -0.0430 | 0.3476 | -1.0380 | 0.5700 |
| ***(**Low < 0)* | *34* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *32* | *1* | *0* | *0* | *1* |
| Negative reciprocity | 66 | -0.0042 | 0.2641 | -0.4893 | 0.6648 |
| ***(**Low < 0)* | *33* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *33* | *1* | *0* | *0* | *1* |
| Risk taking | 66 | 0.0312 | 0.3080 | -0.9396 | 0.9706 |
| ***(**Low < 0)* | *33* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *33* | *1* | *0* | *0* | *1* |
| Altruism | 66 | -0.0104 | 0.3398 | -0.9396 | 0.9065 |
| ***(**Low < 0)* | *27* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *39* | *1* | *0* | *0* | *1* |
| Trust | 66 | -0.0388 | 0.2838 | -0.7064 | 0.6090 |
| **(***Low < 0)* | *27* | *1* | *0* | *0* | *1* |
| *(High > 0)* | *39* | *1* | *0* | *0* | *1* |
| **SDI** | | | | | |
| Low SDI = 1 | 3 | 1 | 0 | 0 | 1 |
| Low-middle SDI =1 | 12 | 1 | 0 | 0 | 1 |
| Middle SDI = 1 | 11 | 1 | 0 | 0 | 1 |
| High-middle SDI = 1 | 21 | 1 | 0 | 0 | 1 |
| High SDI = 1 | 18 | 1 | 0 | 0 | 1 |

Table III describes the preference data used in section 6.2. We have preference data but not SDI data for Russia. Thus, the observations for SDI adds up to 65. SDI is here included for the sole purpose of giving a brief insight to the variance of countries in the preference dataset. Data is retrieved from (Woolridge, 2015) (Wooldridge, Abadie, Athey, & Imbens, 2017), and HEI's website.

# 5. Empirical method

## 5.0.1 Econometric approach

In this thesis, we want to investigate the relation between $PM_{2.5}$ and economic growth. To do this we will utilize three approaches. The first is to estimate the direct relation between $PM_{2.5}$ pollution and GDP using a range of econometric techniques on a panel of countries. The second approach is to investigate if there is a relation between countries' $PM_{2.5}$ levels and a range of economic preferences. The third will utilize the EUs' adoption of $PM_{2.5}$ regulation in 2008 to estimate whether regulatory actions can affect the harmful levels of $PM_{2.5}$.

## 5.0.2 Functional form

Before describing the different econometric approaches, we need to discuss the functional form of our regressions. Our preferred approach is to estimate a log-log model. This functional form has two advantages over using a linear model. Firstly, the log-log model allows us to interpret the estimated coefficients as the elasticity of $PM_{2.5}$ pollution with regard to GDP per capita. By doing so we are able to interpret the estimated coefficients as a 1% change in GDP per capita has a given percentage effect on $PM_{2.5}$ pollution. This makes the interpretation of the results more intuitive. The second benefit is that the log-log approach reduces the impact of outliers by narrowing the range of values in the data (Woolridge, 2015, p.191). This is helpful as there are a few outlier countries with high levels of both $PM_{2.5}$ pollution and GDP per capita. These countries are typically oil producing, heavily desert countries like Saudi Arabia and Bahrain. Since both GDP per capita and $PM_{2.5}$ are strictly positive there is no technical drawback to the logarithmic conversion (Woolridge, 2015, p.191). A third reason for using a logarithmic form is presented by Stern (2004), in that he states "regressions that allow levels of indicators to become zero or negative are inappropriate (…). A logarithmic dependent variable will impose this restriction." Naturally $PM_{2.5}$ pollution has a minimum boundary of zero, and this restriction applies to our analysis.

We also estimate the model with other functional forms to check the sensitivity of our results. Results of these are presented in appendix A with discussions of the implications.

# 5.1 Environmental Kuznets Curve estimations

## 5.1.1 Panel data estimation

To investigate if the proposed inverted U-shaped relationship between economic development and $PM_{2.5}$ pollution is true we use both a fixed effects and a random effects regression model. As stated in the previous section our preferred functional form is a log-log model. To estimate the economic relationship, we use a linear and squared term for GDP per capita. To control for a possible time trend, we include yearly dummies.

We therefore use the following unobserved effects model:

$$\log PM_{2.5_{i,t}} = \beta_0 + a_i + \beta_1 \times \left(\log GDP/P_{i,t}\right) + \beta_2 \times \left(\log GDP/P_{i,t}\right)^2 + \gamma_t + \varepsilon_{i,t}\ , \qquad (\mathbf{1})$$

The dependent variable is the natural logarithm of population weighted $PM_{2.5}$ pollution in country $i$, year $t$. The term $a_i$ captures unobserved non-time varying country specific effects like geography and climate. The $\beta_1$ and $\beta_2$ coefficients estimate the linear and the non-linear effect of GDP per capita on pollution. $\gamma_t$ estimates the time effects and $\varepsilon_{i,t}$ is the idiosyncratic error term. $\beta_0$ is an intercept and represent the sample average country fixed effects. Normally this is not reported when performing fixed-effect estimation as this term is added to the country specific effects. We have chosen to split the two in order to obtain an estimate of the country specific fixed effects independent from the average sample effects. Furthermore, it yields an easily accessible term to interpret effects for the average country.

To estimate turning points, given in GDP per capita, we use the following formula:

$$\exp\left(\frac{-\beta_1}{2\beta_2}\right), \qquad (\mathbf{2})$$

We have also estimated our preferred model using sub samples of countries with either high or low SDI-scores to control for any possible differences between the more and less developed countries, as well to see if there is a joint EKC for the entire world[3]. We also estimated EKCs

[3] Countries classified as high and high-middle SDI countries according to (IHEI, 2018) are grouped to Higher SDI countries. Countries classified as middle, low-middle and low are grouped to Lower SDI countries.

before and after 2010. This is for two reasons. Firstly, as discussed in the outline of the dataset, we only have pollution data for every five years until 2010 and this allows us to control for any possible differences arising from the different in the frequencies of the data. Secondly, we can check if there is a structural break across time in the estimated relation between pollution and economic development.

### 5.1.2 Fixed effects model

The unobserved effects model in (1) becomes the fixed effects model when we time-demean all variables (Woolridge, 2015 p. 387). For each country, *i*, we average the unobserved effects model over time:

$$\overline{\log PM}_{2.5_i} = \beta_0 + a_i + \beta_1 \times \left(\overline{\log GDP/P}_{i,t}\right) + \beta_2 \times \left(\overline{\log GDP/P}_{i,t}\right)^2 + \bar{\gamma} + \bar{\varepsilon}_i$$

where $\overline{\log PM}_{2.5_i} = \frac{\sum_{i=1}^{T} \log PM_{2.5_{i,t}}}{T}$, and so on.

We derive the equation appropriate for OLS regression by subtracting the time-demeaned model from the original unobserved effects model:

$$\log \widetilde{PM}_{2.5_{i,t}} = \beta_1 \times \left(\log \widetilde{GDP/P}_{i,t}\right) + \beta_2 \times \left(\log \widetilde{GDP/P}_{i,t}\right)^2 + \tilde{\gamma}_t + \tilde{\varepsilon}_{i,t}\,, \qquad (\mathbf{3})$$

where $\log \widetilde{PM}_{2.5_{i,t}} = \log PM_{2.5_{i,t}} - \overline{\log PM}_{2.5_i}$, and so on.

We notice that the constant $\beta_0$ and the constant country specific unobserved effects, $a_i$, are eliminated from the time-demeaned equation. The fixed effect method means estimating the time-demeaned equation (3) using pooled OLS. In our estimation, we add the time dummies after doing the time-demeaning. This implies that the estimated time effects accounts for differences to the base year, rather than to an average.

### 5.1.3 Random effects model

While we in the fixed effects estimation only analyse the variation within each country, we also utilize some of the cross-country variation in random effects estimation. That is, we only remove a fraction of the average values when we perform the time-demeaning:

$$\theta\,\overline{\log PM}_{2.5_i} = \theta\beta_0 + \theta a_i + \theta\beta_1 \times \left(\overline{\log GDP/P}_{i,t}\right) + \theta\beta_2 \times \left(\overline{\log GDP/P}_{i,t}\right)^2 + \theta\bar{\gamma} + \theta\bar{\varepsilon}_i$$

The unobserved model becomes the random effects model when we quasi-demean the data:

$$\log P\ddot{M}_{2.5_{i,t}} = \log PM_{2.5_{i,t}} - \theta\,\overline{\log PM}_{2.5_i} = \beta_0(1-\theta) + a_i(1-\theta) + \beta_1 \times \left(\log\frac{GDP}{P}_{i,t} - \theta\,\overline{\log\frac{GDP}{P}}_{i,t}\right) + \beta_2 \times \left(\left(\log\frac{GDP}{P}_{i,t}\right)^2 - \theta\,\overline{\left(\log\frac{GDP}{P}_{i,t}\right)^2}\right) + \gamma_t(1-\theta\overline{\gamma}_t) + \varepsilon_{i,t}(1-\theta)\,, \qquad \mathbf{(4)}$$

where $\log P\ddot{M}_{2.5_{i,t}}$ is the quasi-demeaned $\log PM_{2.5_{i,t}}$, and the parameter $\theta$ is given by

$$0 < \theta = 1 - \left(\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + T\sigma_a^2}\right)^2 < 1\,, \qquad \mathbf{(5)}$$

where $\sigma_\varepsilon^2$ is the variance of the idiosyncratic error terms $\varepsilon_{i,t}$, and likewise for the country specific unobserved time invariant effects $a_i$. We never truly know $\sigma_\varepsilon^2$, $\sigma_a^2$ or $\theta$, but calculate the parameter based on consistent estimators $\widehat{\sigma_\varepsilon^2}$ and $\widehat{\sigma_a^2}$ (Woolridge, 2015 p. 395). These estimators are calculated based on the estimated composite residuals $\hat{v}_{i,t}$ using pooled OLS on the unobserved effects model, where $v_{i,t} = a_i + \varepsilon_{i,t}$.

The random effect method means estimating the quasi-demeaned equation using pooled OLS. In our estimation, we add the time dummies after doing the quasi-demeaning. This implies that the estimated time effects accounts for differences to the base year, rather than to an average.

### 5.1.4 Fixed or random effects?

A key feature of both models is that they fully or partly remove the country specific unobserved effects $a_i$ from the estimation, which otherwise would be captured in the error term. If captured fully by the error term, they would create serial correlation in the residuals, which would hurt the efficiency of the OLS estimators.

The fixed effects estimator is unbiased and efficient under the assumptions that the idiosyncratic error terms, $\varepsilon_{i,t}$, are strictly exogenous, homoskedastic and serially uncorrelated (Woolridge, 2015, p.388).

We test for serial correlation and heteroskedasticity in the idiosyncratic error terms $\varepsilon_{i,t}$. We regress the residuals $\varepsilon_{i,t}$ on one lag of the residuals and perform a t-test on the autocorrelation coefficient. The Breusch-Pagan test tests for violation of the assumption of homoskedastic error terms (Woolridge, 2015, p.220). We regress the squared residuals on the explanatory variables *log GDP/P* and *(log GDP/P)*$^2$ and perform an F-test on the coefficients of the explanatory variables. A null hypothesis of all coefficients equal to zero implies homoskedastic error terms as the explanatory variables do not have a statistically significant effect on the squared residuals.

In a panel dataset, the variance of the residuals may differ across groups, while the error term is still homoskedastic within groups and vice versa. To test for country wise heteroskedasticity in the residuals, $u_{it}$, of the fixed effect models, we use a modified Wald test proposed by Greene (2000, p.235).

For the random effects estimator to be unbiased, in addition to the fixed effects assumptions, the country specific effects $a_i$ have to be independent of all explanatory variables in all time periods (Woolridge, 2015, p.395). The assumption of the fixed effects model is looser in the sense that it allows for correlation between the country specific effects $a_i$ and the income terms.

There are advantages of the random effects model. One is the possibility to include explanatory variables that are constant over time, which with fixed effects estimation would be swept away by the country fixed effects (Woolridge, 2015, p. 399). Furthermore, when the random effects model is estimated consistently it is more efficient than fixed effects as it also utilizes some of the cross-country variance, where fixed effects only uses the within-country variance. Woolridge (2015, p.399) pinpoints however, that country time-invariant effects which truly are unrelated to the explanatory variables are rare.

From the random effects model, we can see that when $\theta$[4] $\rightarrow 1$, the random effect estimators of the income terms and error term go towards the estimators and error term of the fixed effects

[4] See (5) section 5.1.3

model[5] (Woolridge, 2015, p. 397). The smaller the $\theta$, the larger fraction of the unobserved effect is left to the error term in the random effects model, and the larger the asymptotic bias of the random effects estimator. When the variance of $a_i$ is small relative to the variance of the idiosyncratic error term $\varepsilon_{it}$, $\theta$ tends to 1. Following, the bias term goes to zero as the random effects estimator tends to the fixed effects estimator which is unbiased under the fixed effects assumptions. Hence, to formalize the consideration between the two models, we test for statistically significant differences in the coefficients of the time-varying explanatory variables (*log GDP/P*, *(log GDP/P)*$^2$ and *year)* between the two models, using the Hausman (1978) test (Woolridge, 2015, p.399). The test's null hypothesis is that differences between the coefficients are not systematic, and thus that there is not a significant difference between the two models. If we fail to reject this, the RE model is generally preferred as it is more efficient.

### 5.1.5 Clustering

The default t-statistics and standard errors of the explanatory variables in panel data estimations, rely on the assumption of independently and identically distributed (i.i.d.) error terms. In economic cross-country analysis, there are often reasons to suspect error terms to be serially correlated and heteroskedastic as observations are not independently drawn. In the presence of heteroskedastic and serially correlated error terms it can be shown that the estimator is still unbiased, but the standard errors and test statistics will not be valid (Williams, 2015).

A common approach to escape this inference issue and obtain robust standard errors in empirical work in economics is to cluster on units (Wooldridge, Abadie, Athey, & Imbens, 2017). Woolridge et. al. (2017) argues that the decision of clustering or not should not be based solely on whether it makes a difference on the standard errors, but also on a careful discussion if it is meaningful. Specifically, the authors conclude that one should cluster if either sampling or treatment was clustered[4].

[5] When $\theta \rightarrow 1$, (4) given by; $y_{it} - \theta\bar{y}_{it} = \beta_0(1-\theta) + \beta_1(x_{it1} - \theta\bar{x}_{it1}) + ..$ $+ \beta_k(x_{itk} - \theta\bar{x}_{itk}) + (v_{it} - \theta\bar{v}_i)$, where $(v_{it} - \theta\bar{v}_i) = (1-\theta)a_i + \varepsilon_{it} - \theta\bar{\varepsilon}_{it}$, goes toward $y_{it} - \bar{y}_{it} = +\beta_1(x_{it1} - \bar{x}_{it1}) + .. + \beta_k(x_{itk} - \bar{x}_{itk}) + (\varepsilon_{it} - \bar{\varepsilon}_{it})$ which is the FE model (3).

As our sample of 1884 observations on $PM_{2.5}$ concentrations are not randomly drawn, but rather a selection of 12 annual observations for 157 countries, we view our sampling to be clustered on countries. By clustering on countries, we loosen up on the assumption of independent observations, and allow for correlation within countries. We thereby obtain robust standard errors, accounting for serial correlation and heteroskedasticity in the error terms.

If the assumption of i.i.d. error terms is violated, the default standard errors are likely to be downwards biased (Cameron & Miller, 2015). By allowing for within-country correlation between observations, the clustered standard errors are the inflated i.i.d. standard errors with an approximate factor;

$$\sqrt{1 + \rho_x \rho_\varepsilon (\bar{N} - 1)}\,,$$

where $\rho_x$ is the within-country correlation between the observations of the explanatory variable $x$, $\rho_\varepsilon$ is the within-country error correlation, and $\bar{N}$ is the average number of observations within each cluster (Cameron & Miller, 2015). Explanatory variables are the income terms, *log GDP/P* and *(log GDP/P)*$^2$, and the error correlation the correlation between the idiosyncratic error terms $\varepsilon_{i,t}$. Thus, from the inflation factor we notice that inference is more difficult for groups of countries where error terms or/and observations of income terms are more correlated, as clustered standard errors increase more.

### 5.1.6 Non-stationarity and co-integration

In analysis of time series, there might be found relationships between indicators which are in reality unrelated. This may happen when two series follow a similar underlying trend or movement. Observations of such series are impacted by previous observations. We call these series non-stationary (Woolridge 2015, p. 306).

Use of non-stationary series might lead to spurious results. That is the regressions results indicate relationships that are truly non-existing. An easily accessible example is number of drownings and ice cream consumption. Of course the true effect of ice cream consumption on drownings is zero, but because both increase during summer the regression results might indicate a significant relationship.

Some non-stationary series are also highly-persistent. That is that the series follow a random walk, where the covariance between $y_t$ and $y_{t-1}$ is close to one. The series is then said to have a unit root. Unit root series might be stationary after first-differencing[6]. Such series are said to be integrated of order one.

The problem of non-stationarity and spurious results might be eliminated if both series used are non-stationary co-integrated. If both series are integrated of order one it they might cancel each other out. The residuals of the regression model will then be stationary, and we do not need to worry about spurious results.

*Log GDP/P* and *log $PM_{2.5}$* are series that might be non-stationary. If they are co-integrated however, and the residuals in (1) is stationary, we can use them in our regression without the risk of spurious results (Woolridge 2015, p. 512). We investigate for unit root of all explanatory variables, independent variables and the residuals $\varepsilon_{i,t}$ using a modified Dickey Fuller test for panel data with large N and fixed T[7] (Harris, et. al., 1999). It tests if $\theta$ is significantly different from 0 in;

$$\triangle y_{it} = a + \theta y_{it-1} + e_t$$

$$\text{where } \triangle y_{it} = y_{it} - y_{it-1}$$

where $y_{it}$ is the variable we test, i.e. *log GDP/P*, *log $PM_{2.5}$* and the residuals $\varepsilon_{i,t}$ from the panel estimation. If $\theta$ is zero, the tested variable $y$ follows a random walk and is non-stationary. Thus if $\theta$ is significantly different from zero we reject a null hypothesis that the series is non-stationary. If *log GDP/P* and *log $PM_{2.5}$* co-integrate and the residuals are stationary, we do not have indications of spurious results.

### 5.1.7 Chow test

In order to test for differences between developed and developing countries, or a structural change across time, we utilize the Chow test. Allowing for different intercepts across groups, the Chow test is a F-test which tests for statistically significant differences in the coefficients of the income terms. This allows us to see (1) if the estimated model is the same for the entire

[6]The first-differenced of y is given by; $\triangle y_t = y_t - y_{t-1}$

[7] N is number of countries and T is number of years.

world, or if there are differences in the estimated paths of developed and developing countries, and (2) if there is a structural break in time.

The null hypothesis of the Chow test is that all slope coefficients are equal. Formally, we estimate the fixed or random effects model based on the equation:

$$\log PM_{2.5_{i,t}} = \beta_0 + a_i + \beta_1 \times \left(\log GDP/P_{i,t}\right) + \beta_2 \times \left(\log GDP/P_{i,t}\right)^2 + \delta_1 \times \left(\log GDP/P_{i,t}\right) \times Subsample_{it} + \delta_2 \times \left(\log GDP/P_{i,t}\right)^2 \times Subsample_{it} + \gamma_t + \varepsilon_{i,t}, \qquad (\mathbf{6})$$

When testing for differences across groups, *Sub sample,* is a dummy variable taking the value 1 if country *i* is part of the sub sample of higher SDI countries, zero if not. Likewise, when testing for structural breaks across time, *Sub sample*, takes the value 1 if the observation is from 2011 or later.

To conclude whether there is a statistically significant difference between the estimated curves, the Chow test performs a joint significance test of the coefficients of the income terms, $\delta_1$ and $\delta_2$. The null hypothesis is that both are equal to zero and that pooling the groups of observations do not affect the estimated EKC significantly. A rejection of the null hypothesis thus implies that there is not a statistically significant (I) difference in the estimated EKC across groups, or (II) structural change across time.

## 5.2 Estimating with preferences

In the previous section, we outlined our preferred method of estimating the EKC. When performing the fixed effects estimation, we obtain a parameter that captures time invariant pollution levels in a given country. Assuming that preferences are constant over time we know that the potential effect of these are captured in this term. We can explore how much of the country specific effect on $PM_{2.5}$ pollution can be explained by differences in economic preferences.

### 5.2.1 Ordinary least squares

There are data on preferences for 66 countries, measured in 2012, in our dataset. We assume these preferences to be constant over time. Under this assumption, we can investigate if preferences can explain some of the variation in the country fixed effects. Utilizing a cross-sectional dataset with information on country fixed effects, patience, positive and negative reciprocity, altruism, trust and risk taking, we perform a multiple regression analysis on the country fixed effect of pollution using the ordinary least squares method:

$$a_i = \beta_0 + \beta_1 \times patience_i + \beta_2 \times pos.reciprocity_i + \beta_3 \times neg.reciprocity_i + \beta_4 \times risk\ taking_i + \beta_5 \times altruism_i + \beta_6 \times trust_i + \varepsilon_i\ , \qquad (\mathbf{7})$$

where the dependent variable $a_i$ is the country fixed effects for the 66 countries with preference data in our dataset, retrieved from the fixed effects model run on the full sample from Table IV[8]. As the country fixed effects are measured in natural logarithms of $PM_{2.5}$ exposure, the interpretation of the coefficients of the explanatory variables is that a unit increase in preference score $k$ leads to $ß_k$ units increase in the country fixed effects, implying a $ß_k$ percentage increase in the non-time varying levels of $PM_{2.5}$ concentration in country $i$. $ß_0$ is an estimated intercept and does not have a meaningful interpretation in this model. $ß_0$ to $ß_6$ are chosen simultaneously to minimize the sum of the squared error terms $\varepsilon_i$ (Woolridge, 2015, p.61). Under the five Gauss-Markov assumption our estimated coefficients $\widehat{\beta_0}, \widehat{\beta_1}, \dots \widehat{\beta_6}$ are the best linear unbiased estimators of the true effects $ß_0$, $ß_1$,…, $ß_6$ (Woolridge, 2015, p.90).

## 5.2.2 Model specification

Decisions of including or excluding additional explanatory variables should be based first and foremost on the purpose of the estimation, and thereafter on a consideration of the trade-off between efficiency and bias (Woolridge, 2015, p.86). We should therefore always consider which effects we want our model to estimate.

If we are only interested in the effect of e.g. patience, we do not care about correlation between positive reciprocity and altruism. If we however also care about the effect of positive reciprocity and altruism on the country effects, we need to analyse the trade-off between efficiency and bias.

The trade-off between efficiency and bias relies on the true effect of the explanatory variables on the dependent variable. If the true value $ß_k$ equals zero, then it should be excluded as it cannot help explaining variance in the country fixed effects, $a_i$. It can only increase

[8] The country fixed effects are listed in Appendix A, table A-V. Country fixed effects used for the preference estimations are listed in column 1.

multicollinearity, correlation between explanatory variables, and lead to less efficient estimators (Woolridge, 2015 p.86). If the true value $ß_k$ is non-zero however, the question is more complex where including the explanatory variables may lead to inefficient estimators due to multicollinearity, and exclusion may lead to omitted variable bias in estimators due to ignoring true effects.

As we are interested in the effects of several of the preferences, we might face multicollinearity problems. To test for the severity of the multicollinearity we calculate the variance inflation factor (VIF). The variance inflation factor for explanatory variable $k$ is given by $VIF_k = 1/(1 - R_j^2)$, where $R^2_j$ is the R-squared from regressing $x_j$ on all other explanatory variables. However, there is no clear cut-off value for which multicollinearity is a severe problem. A common rule of thumb in empirical works in economics is that values below 10 indicates that the estimations do not suffer from multicollinearity (Brooks, 2004).

Finally, the choice of model specification is based on a consideration if we believe there exists a meaningful relation between the preference variable and the country fixed effects of pollution.

## 5.3 Difference in difference and the effect of EU law

In 2008 the EU implemented Directive 50 (EU, 2008). We can exploit this to perform a difference-in-difference estimation to investigate whether the regulation has had an effect on $PM_{2.5}$ levels in member countries. When estimating the effect, we are comparing the trend before and after the implementation in EU countries to (I) the full sample and (II) the sub sample of socio-economically developed countries.

The difference-in-difference method allows us to account for differences between the EU countries and the comparison groups which were already in place before the directive. Thus, the method seeks to estimate the isolated effect the directive has had on $PM_{2.5}$ pollution in EU countries. We estimate the following equation:

$$\log PM_{2.5_{i,t}} = \beta_0 + \beta_1 \times EU_i + \beta_2 \times (Post\ 2008_t) + \beta_3 \times (EU\ post\ 2008_t) + \beta_4 \times v + \gamma_t + \varepsilon_{i,t}\ , \qquad \textbf{(8)}$$

Where $\log PM_{2.5_{i,t}}$ is the natural logarithm of the $PM_{2.5}$ pollution in country *i* in year *t*. $EU_i$ is a dummy taking the value 1 if country *i* is part of the EU, and 0 if not. Post $2008_t$ is a dummy taking the value 1 if the observation is for a year post year of policy implementation, 2008, 0 if not. EU post $2008_{i,t}$ is a dummy taking the value 1 if country *i* is part of the EU and year, *t*, of the observation is post policy implementation. $\gamma_t$ is the time effects, equal across countries. $\varepsilon_{i,t}$ is the residuals and *v* a vector of other control variables.

The constant $\beta_0$ is the average $PM_{2.5}$ mean exposure before 2008 for countries which are not part of the EU. $\beta_1$ captures the average difference between $PM_{2.5}$ exposure in a EU country and a non-EU country before 2008. $\beta_2$ expresses the average trend in a non-EU country after 2008. $\gamma_t$ are the time effects, v is a vector of other control variables unrelated to the directive, and ε is the error term. The coefficient $\beta_3$, known as the DiD-estimator, is the main variable of interest. The DiD-estimator can be expressed as (Woolridge, 2015 p.367):

$$\widehat{\beta_3} = \left(\overline{\log PM_{2.5}}_{\,a2008,EU} - \overline{\log PM_{2.5}}_{\,a2008,non-EU}\right) - \left(\overline{\log PM_{2.5}}_{\,b2008,EU} - \overline{\log PM_{2.5}}_{\,b2008,non-EU}\right)$$

where subscript b2008 and a2008 indicates before and after 2008 respectively. The DiD-estimator thereby captures the difference in the average trend after 2008 between EU countries and non-EU countries. Under a ceteris paribus assumption, the DiD-estimator is thus able to capture the isolated effects of the 2008 directive on $PM_{2.5}$ pollution in EU (Woolridge, 2015 p.367).

In the simplest form of the model, we are not controlling for other variables than time effects, i.e. $v = 0$ in (8). To account for possible presence of an EKC, or at least a relationship between $PM_{2.5}$ and GDP, we sophisticate our model by including for linear and non-linear relationships with the natural logarithm of GDP per capita. Main variable of interest is still the DiD-estimator however, and additional control variables should only be seen as instruments to make this estimator more efficient and plausible.

# 6. Results

In this part, we will present the estimation results before discussing them further in chapter 7. In section 6.1 we present our results from estimating an EKC for $PM_{2.5}$.

First, we present the results for the full sample, and look for differences between developed and developing countries. Following this we estimate World EKCs based on observations from different time spans and look for a structural break in time.

In section 6.2, we use preference data to explain differences across time invariant country specific levels of $PM_{2.5}$. We also group countries according to preferences, and use the fixed and random effects model to investigate if there are different EKCs for these groups.

In 6.3 we utilize the difference-in-difference estimation method to investigate whether the EU directive of 2008 on $PM_{2.5}$ had an effect on pollution levels in member states.

## 6.1 Environmental Kuznets Curve for $PM_{2.5}$

### 6.1.1 Estimated EKCs and differences across groups

Table IV presents the results from estimating (1). Columns 1,3 and 5 show the results from a fixed effects estimation and columns 2, 4, and 6 show results from the random effect estimation. Columns 1 and 2 show the results for the whole sample, while 3 and 4 show the results for countries with a higher SDI score and 5 and 6 for countries with a lower SDI score.

We will refer to the two sub samples as developed and developing countries from now on, except in tables and figures.

TABLE IV
Regression results
1990-2017
(log-log)

| Region | World $N = 157$ | | Higher SDI $N = 77$ | | Lower SDI $N = 78$ | |
|---|---|---|---|---|---|---|
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | 0.4177$^{***}$ | 0.4377$^{***}$ | 0.2674 | 0.3252 | 0.2782$^{***}$ | 0.2630$^{**}$ |
| | (4.68) | (4.77) | (1.19) | (1.43) | (2.47) | (2.36) |
| $(\ln GDP/P)^2$ | -0.0240$^{***}$ | -0.0260$^{***}$ | -0.0140 | -0.0179 | -0.0164$^{**}$ | -0.0156$^{**}$ |
| | (-4.69) | (-4.95) | (-1.18) | (-1.50) | (-2.49) | (-2.39) |
| Constant | 1.4496$^{***}$ | 1.4295$^{***}$ | 1.7041 | 1.5013 | 2.3104$^{***}$ | 2.3790$^{***}$ |
| | (3.73) | (3.53) | (1.60) | (1.39) | (4.83) | (4.98) |
| Turning point | 6,015 | 4,525 | 14,045 | 8,811 | 4,826 | 4,580 |
| *p* | 0.705$^{***}$ | 0.703$^{***}$ | 0.661$^{***}$ | 0.658$^{***}$ | 0.677$^{***}$ | 0.678$^{***}$ |
| AR(1) | (35.92) | (35.80) | (22.24) | (22.13) | (24.25) | (24.25) |
| Dickey-Fuller | 0.7257$^{**}$ | 0.7223$^{***}$ | 0.6950$^{***}$ | 0.6913$^{***}$ | 0.6868$^{***}$ | 0.6869$^{***}$ |
| test[1] | (0.0102) | (0.0062) | (0.0028) | (0.0018) | (0.0010) | (0.0010) |
| Breusch-Pagan | 3.42$^{**}$ | 3.40 | 0.66 | 0.68 | 4.13$^{**}$ | 4.19$^{**}$ |
| test | (0.0330) | (0.337) | (0.5160) | (0.5072) | (0.0164) | (0.0155) |
| Wald test | 10,726$^{***}$ | | 25,265$^{***}$ | | 2,775.1$^{***}$ | |
| | (0.0000) | | (0.0000) | | (0.0000) | |
| Chow F-test | 1.05 | 3.18 | | | | |
| | (0.3526) | (0.2043) | | | | |
| Hausman test | | 38.79$^{***}$ | | 27.98$^{***}$ | | 3.56 |
| | | (0.0000) | | (0.0000) | | (0.1688) |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1884 | 1884 | 924 | 924 | 936 | 936 |
| Adjusted. $R^2$ | 0.3260 | | 0.6306 | | 0.1334 | |

Table IV shows results from estimating unobserved effects (1) for the full sample period 1990-2017. Dependent variable is the level of population weighted mean exposure to $PM_{2.5}$, in country *i* in year *t*, in natural logarithms. Figures in parentheses are *t* statistics for regression coefficients and significance levels for the Dickey-fuller, Breusch-Pagan, Wald, Chow and Hausman test statistics. *t* statistics are calculated based on robust standard errors that allow for within-country correlation. Turning points are in 2011 purchasing power parity international dollars. AR(1) is a t-test on the residual autocorrelation coefficient *p*. $H_0$ in Breusch-Pagan and Wald[2] tests is homoskedastic error terms. $H_0$ in the Chow F-test is that all slope coefficients are equal across classification groups. The null hypothesis of the Hausman test is that RE estimators are unbiased. The Hausman test is performed using covariance matrices based on the estimated disturbance variance from the consistent estimator. Bahrain and Saudi-Arabia are excluded from the Higher SDI sample, and Russia is included in the Lower SDI sample. [1] The DF-test finds that *log GDP/P* and *log* $PM_{2.5}$ are integrated of order one. [2]Within-country homoskedasticity
Significance levels: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Estimating for the full sample, we find evidence for an EKC. The linear term is positive and the squared term negative, which satisfies the properties of the hypothesised relationship.

The estimated coefficient for the linear term is 0.4177 meaning that a 1 % increase in income changes pollution by 0.4177 %. The estimated coefficient for the squared term is -0.0240 meaning that a 1 % increase in income causes a change in pollution by -0.0240 times the squared value of the log of income. The total effect of income on pollution is the sum of these two terms. For the world sample, the greatest level of $PM_{2.5}$ pollution is reached at $6,015. For countries with larger income than the estimated turning point pollution levels decline when income increases. For the World estimation, presented in column 1, the results are significant at the 1 % level for both income terms and the estimated constant, which is the sample average country effect.

For the World EKC results in columns 1 and 2, both the Wald-test and Breusch-Pagan test indicate presence of heteroskedasticity. Results of AR(1) test indicate that the residuals are autocorrelated. To control for this, we base inference on clustered standard errors. The Hausman-test suggests that the random effects estimators are biased, and that we should prefer the fixed effects model.

We believe the estimated results is evidence of a true relationship between pollution and income. For all periods, the Dickey-Fuller rejects unit roots in the first-differenced of *log* $PM_{2.5}$ and *log GDP/P*. There is thus evidence that both are integrated of order one and therefore co-integrated. It also rejects unit root in the residuals of the panel estimations, and we do not have indications of spurious results.

***Main result 1:*** *Our full sample estimation finds evidence for an EKC for* $PM_{2.5}$ *in the period 1990-2017.*

For developed countries none of the estimated coefficients are significant. When looking at the result for the Wald-test we see that the test score is very high, which indicates severe within-country heteroscedasticity. This inflates the clustered standard errors and makes inference more difficult. If we make inference based on the regular standard errors we get the result that both income terms are statistically significant. However, these results might be spurious. For qualitative considerations discussed in 5.1.5, we believe standard errors should be clustered, and thus prefer these results despite statistically insignificant results.

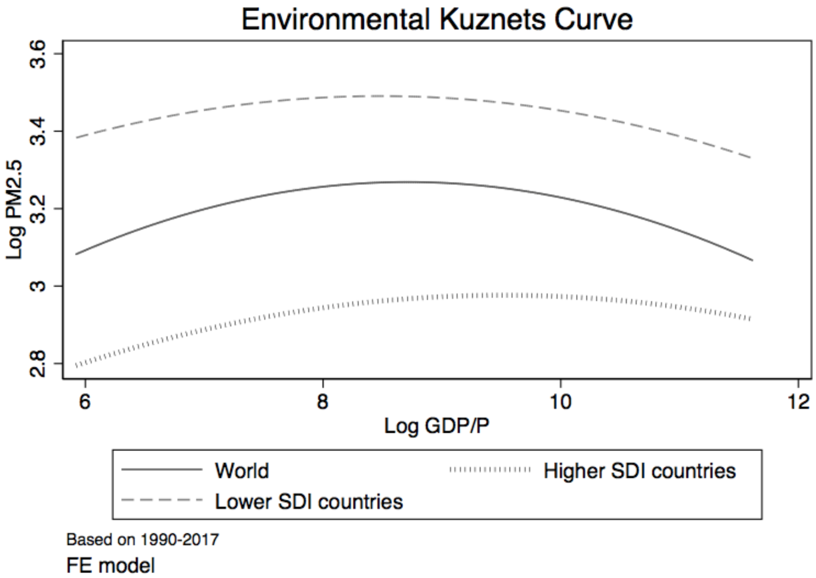
However, it may still be useful to consider the estimated coefficients. The results for the developed countries follow the same general pattern as the estimation for the whole sample. The linear term is positive while the squared term is negative. The turning point given by the estimated coefficients amounts to $14,085. However, the level of pollution at the turning point is lower than for the world sample, but as the coefficients are not significant we cannot say whether there is in fact a true turning point.

For developing countries, the Hausman-test indicates that we cannot reject that the estimated coefficients from the FE and RE are equal. Normally we would prefer the random effects model in this case as it is considered more efficient than the fixed effect model, but we believe that there are country specific characteristics that correlate with income. It seems rather unlikely that all country specific unobserved effects would be uncorrelated to GDP, which works a proxy for all economic activity in a country. Therefore, we prefer the fixed-effects model as it allows for this correlation. There are indications of heteroscedasticity and autocorrelation in the residuals.

The estimated coefficients in column 5 are 0.2782 for the linear income term and -0.0164 for the squared term. The estimated turning point of $4,826 for developing countries is lower than for the full sample, but implies greater levels of pollution for the average country.

Figure IV illustrates the estimated World EKC along with the EKCs for developed and developing countries. When comparing the estimated EKCs we see that the curve for developing countries is flatter, have a lower turning point and greater levels of pollution for all levels of income. This is most likely due to developing countries having greater levels of pollution than the sample average. The estimated curve for developed countries is lower for the same reasons as developing countries EKC is higher. The turning point is above the sample average and the level of pollution is lower for every level of income.

Figure IV



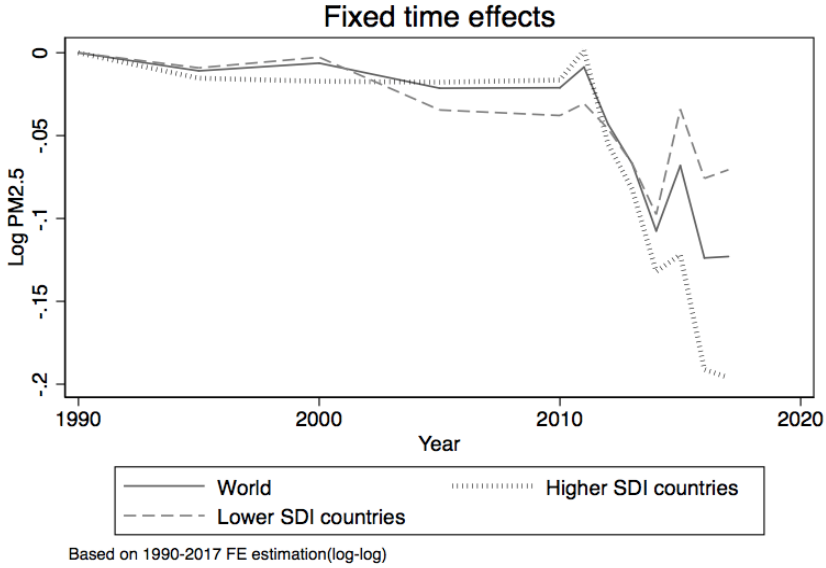

EKC estimations from the fixed effects model using all obs. 1990-2017 for full sample and the two samples. Log-log model. See table I. Note that the time effects are excluded.

We cannot reject that there is a single World EKC, as the Chow-test cannot reject that the estimated slope coefficients are equal for developed and developing countries. This implies that we should disregard the estimated EKCs for developing and developed countries. The World EKC is more sensitive to changes in income, meaning that economic growth has greater impacts on pollution in the World EKC than in the developed and developing countries EKC.

***Main result 2:*** *We do not find evidence that economic growth has greater effects in developed or developing countries, and we thus believe there is a World EKC for fine particulate matter.*

The fixed effects model also yields estimations of the country invariant time effects. This is illustrated in Figure V. The fixed time effects show the country independent changes in pollution levels. Changes are relative to the base year of 1990, and allows for a stochastic trend. These time effects can be viewed as technological progress. We see that the time effects have been greater in developed countries in recent times. This might be an indication that the technological progress across developed countries has increased relative to developing countries.

Figure V




Fixed time effects for World, Higher SDI countries and Lower SDI countries EKC for the log-log model using all observations 1990-2017. Expressed in logarithmic differences in $PM_{2.5}$ exposure relative to the base year 1990.

### 6.1.2 Structural break in time

Table V presents the results from estimating (1) for different time periods. Columns 1,3 and 5 show the results from a fixed effects estimation and columns 2, 4, and 6 show results from the random effect estimation. Columns 1 and 2 show the results for the whole sample over the entire period. Columns 3 and 4 show the estimation for the period 1990-2010. Columns 5 and 6 show the estimation for the period 2011-2017. The estimations in columns 1 and 2 in Table V is the same as the estimations in columns 1 and 2 in Table IV.

Table V
Regression results
World
(log-log)

| | **World** $N$ **= 157** | | | | | |
|---|---|---|---|---|---|---|
| *T* | **1990 - 2017** $n$ **= 1884** | | **1990 - 2010** $n$ **= 785** | | **2011 - 2017** $n$ **= 1099** | |
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | 0.4177$^{***}$ (4.68) | 0.4377 (4.77) | -0.0154 (-0.15) | 0.0183 (2.88) | 1.4421$^{***}$ (2.60) | 1.3040$^{***}$ (2.92) |
| (ln GDP/P)$^2$ | -0.0240$^{***}$ (-4.69) | -0.0260 (-4.95) | 0.0026 (0.41) | -0.0005 (-0.08) | -0.0906$^{***}$ (-2.97) | -0.0843$^{***}$ (-3.42) |
| Constant | 1.4496$^{***}$ (3.73) | 1.4295 (3.53) | 3.1706$^{***}$ (7.01) | 3.1151$^{***}$ (5.25) | -2.2702 (-0.90) | -1.6451 (-0.82) |
| Turning point | 6,015 | 4,525 | 19(-) | 88631688 | 2,860 | 2,285 |
| *p* AR(1) | 0.705$^{***}$ (35.92) | 0.703$^{***}$ (35.80) | 0.425$^{***}$ (10.90) | 0.423$^{***}$ (10.89) | 0.577$^{***}$ (21.16) | 0.581$^{***}$ (21.20) |
| Dickey-fuller test[1] | 0.7257$^{**}$ (0.0102) | 0.7223$^{***}$ (0.0062) | 0.5952[2] 0.9928 | 0.5852[2] (0.9858) | 0.6296[2] (0.9580) | 0.6316[2] (0.9630) |
| Breusch-Pagan test | 3.42$^{**}$ (0.0330) | 3.40$^{**}$ (0.0337) | 7.34$^{***}$ (0.007) | 8.60$^{***}$ (0.002) | 4.78$^{***}$ (0.0086) | 4.69$^{***}$ (0.0094) |
| Wald test | 10,726$^{***}$ (0.0000) | | 48,177$^{***}$ (0.0000) | | 21,844$^{***}$ (0.0000) | |
| Chow *F*-test | 7.50$^{***}$ (0.0008) | 15.17$^{***}$ (0.0005) | | | | |
| Hausman test | | 38.79$^{***}$ (0.0000) | | 55.88$^{***}$ (0.0000) | | 38.79$^{***}$ (0.0000) |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1884 | 1884 | 785 | 785 | 1099 | 1099 |
| Adjusted. $R^2$ | 0.3260 | | 0.0547 | | 0.2812 | |

Table V shows the results from estimating (1) for the World sample over different sub periods. Dependent variable is log $PM_{2.5}$, in country *i* in year *t*. Figures in parentheses are *t* statistics for regression coefficients and significance levels for the Breusch-Pagan, Wald, Chow and Hausman test statistics. *t* statistics are calculated based on clustered standard errors. Turning points are in 2011 purchasing power parity international dollars. AR(1) is a t-test on the residual autocorrelation coefficient *p*. $H_0$ in Breusch-Pagan and Wald[3] tests is homoskedastic error terms. $H_0$ in the Chow F-test is that all slope coefficients are equal across classification groups. The null hypothesis of the Hausman test is that RE estimators are unbiased. The Hausman test is performed using covariance matrices based on the estimated disturbance variance from the consistent estimator. [1]*log GDP/P* and *log* $PM_{2.5}$ are integrated of order one. [2] Using Kao (1999) co-integration we find evidence for co-integration. [3]Within-country homoskedasticity. Significance levels: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

We do not find evidence for an EKC relationship in the sub period 1990-2010, as none of the income terms are significant or jointly significant. The fixed-effect model estimates a negative linear term while the squared term is positive. The estimated turning point is \$19, which contrary to the other turning points is a minimum point. There are indications of autocorrelation, within-country and cross-country heteroskedasticity. The Hausman-test indicates that the RE estimators are biased. Since the estimated coefficients are not significant we cannot make any statements on the relationship between income and pollution in the period between 1990 and 2010.

We find an EKC for $PM_{2.5}$ in the sub period 2011–2017, as both income terms are statistically significant at the 1 % level. The linear income term is 1.4421, while the squared income term is -0.0906. The 2011-2017 EKC has a turning point of \$2,860. There is presence of heteroskedasticity and autocorrelation, and we base inference on clustered standard errors. The Hausman test indicates that we cannot reject that the RE and FE estimators are equal, but we still prefer the fixed effects model as we believe there are country specific fixed effects correlated to income.

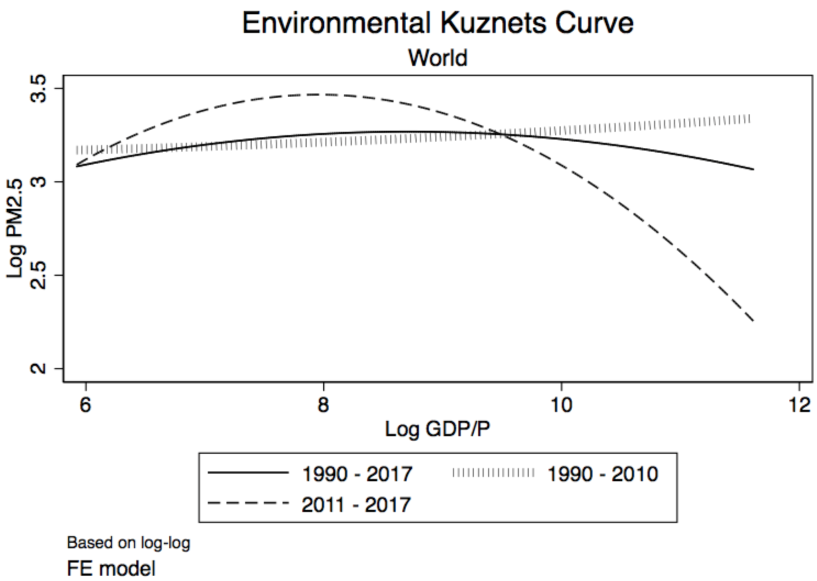
We find evidence for a structural break in time. The Chow-test rejects that the slope coefficients are equal for the two sub periods. This means that the EKC estimated after 2010 is statistically different from an EKC based on the whole period. When comparing the estimated EKCs for 2011-2017 and the full sample, we see that the 2011-2017 EKC is steeper.

The estimated pollution at the turning point is slightly higher for the 2011-2017 EKC, but as the eventual negative income effect is greater, since the curve is steeper the decline in pollution will be more rapid in this period than in the period as a whole, as illustrated in Figure VI. This suggests that poorer countries struggling with elevated $PM_{2.5}$ pollution levels will experience a sharper decline in $PM_{2.5}$ pollution as they develop compared to the past. However, it also suggests that the poorest countries will experience higher levels of pollution than earlier estimated on their way there all else equal.

***Main result 3:*** *We find evidence that the EKC for $PM_{2.5}$ has changed over time. Income growth had greater effects in the sub period 2011-2017 than in the period 1990-2017 as a whole, and the turning point is reached at an earlier stage of economic growth.*

Though we cannot reject unit roots in the residuals, we believe the estimated results is evidence of a true relationship. For the world sample in the whole period, the Dickey-Fuller rejects unit roots in the first-differenced of *log* $PM_{2.5}$ and *log GDP/P*. There is thus evidence of co-integration. However, non-stationary residuals might lead to spurious results. We do however not believe this is present as the results are consequently pointing in the same direction different sub samples across different time periods[9].

Figure VI




World EKCs from the fixed effects model based on different time periods. Log-log model See Table V. Note that the time effects are excluded.

[9] See Table IV together with Table V, A-III and A-IV.

### 6.1.3 Back-of-the-envelope calculations on the matter of time frames for the EKC estimations in the example of Bangladesh

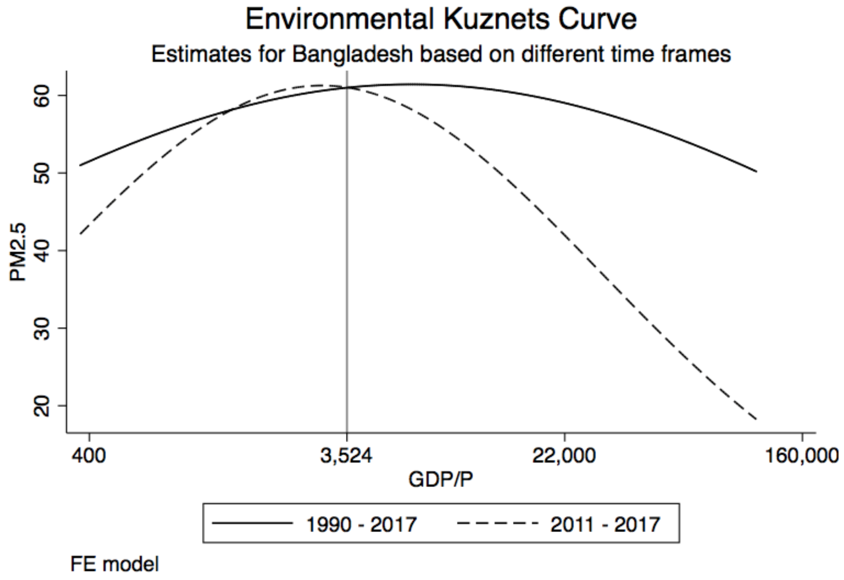
To illustrate the implications of using different time frames for the EKC estimations, we highlight Bangladesh. Bangladesh is among the ten biggest countries in the world with a population of approximately 165 million people[10]. They are less developed and struggle with high levels of pollution. In 2017, the mean exposure of $PM_{2.5}$ was 61 μg/m$^3$, which is far above all recommended levels.

In the previous section we showed that the EKC changes shape depending on which time period one uses. Specifically, if one estimates the curve based only on data from the seven last years in the sample, the curve is steeper but turns faster than a curve based on observations from the whole period. This has several important implications. Firstly, for less wealthy countries it matters for the predicted consequences of economic growth. According to the "old" EKC (1990-2017), they are yet to reach the turning point, which means that we expected air quality to decrease with economic growth. If one rather base predictions on the "new" EKC (2011-2017), they might have already passed the turning point. In that case, further economic growth will improve air quality. One such country is Bangladesh.

With an income of $3,524 in 2017, Bangladesh is in between the estimated turning points of the two EKCs. Figure VII illustrates the differences between the EKCs based on the full time period and the last seven years. The solid line is Bangladesh' estimated EKC based on the full sample, while the dashed line illustrates the EKC estimated on data between 2011 and 2017. The figure illustrates estimated levels of annual mean pollution in Bangladesh on the vertical axis for given levels of economic growth on the horizontal axis. A vertical reference line is included to mark Bangladesh' level of GDP per capita in 2017. We adjust the intercepts of both models such that both curves go through the true values of Bangladesh anno 2017 with 61 μg/m$^3$ $PM_{2.5}$ pollution and income of $3,524. The slopes are unaffected and the adjustment enables us to easier read the consequences of economic growth in true values.

[10] World Bank Group Development Indicators

Figure VII




Estimated EKCs for Bangladesh from the fixed effects model based on different time periods. Log-log model See Table V. Note that time effects are excluded.

The “new” EKC predicts an immediate and greater decline in pollution in Bangladesh with further economic growth.  This is opposite of the “old” estimates, which predicts a period of worsened air quality with economic growth. Furthermore, even after reaching the turning point, the “old” estimate predicts only a small decrease in pollution levels. Even at a level of economic development at $160,000 of income, the “old” EKC predicts pollution levels above 50 μg/m$^3$. Thus, though it predicts increase in air quality eventually, it does not present a great outlook for Bangladesh’ air quality. Though the “new” EKC predicts greater and immediate increases in air quality, it still takes time to reach acceptable levels.

As an example, let us assume Bangladesh will experience yearly economic growth of 2 % the next twenty years, increasing their income to approximately $5,200. Following the EKC based on the full period, pollution will then increase to 61.4 μg/m$^3$, all else equal. For the same economic growth, the EKC estimated on the more recent data predicts pollution to decrease to 59.3 μg/m$^3$. Thus, we see that the estimated decrease is more than four times the size of the estimated increase, but that pollution all in all remains rather stable.

New estimates, based only on post 2011 data, gives reasons to be more optimistic about air quality in Bangladesh. They predict immediate and sharper decreases in pollution with economic growth. We see however, that the effects on absolute pollution levels are rather small for reasonable levels of economic growth in the short term. This implies that Bangladesh, and other countries, also rely on cross border technological progress.

## 6.2 Effects of preferences

In this section we present our approach to explain differences in estimated EKCs, based on cross-country differences in preference measures. We thus seek to explain differences between countries by behavioural characteristics of populations. In doing so, the analysis takes two different approaches. In the first section, we use the parameters of country fixed effects estimated in 6.1 and estimate the effect of six measures of preferences on these time invariant country fixed effects of pollution. In the second section, we go back to the fixed and random effects methods and perform the estimation on sub samples of countries grouped according to preferences. While the first part investigates preferences' effect on the country specific intercepts of the EKC, the fixed and random effects methods allow us to investigate whether preferences affect the shape of the curve.

A brief explanation of the six preference parameters was given in Table I. A more detailed description from Falk et.al. (2018) is reported in the appendix.

### 6.2.1 Preferences and country fixed effects

This section presents results from the multiple regression analysis seeking to explain the cross-country variation in time invariant levels of pollution by behavioural characteristics of populations. This is done by regressing scores for six different preference measures from Falk (2018) on the country fixed effects retrieved from the World EKC model in Table IV. The multiple regression is based on equation (7) for the 66 countries in the Falk sample. We add explanatory variables one by one according to their raw correlations with country effects. The results are presented in Table VI and discussed in the following paragraphs.

When reading the results, one should bear in mind the magnitude of the underlying values of both the dependent and independent variables. Country fixed effects are given in natural logarithms and vary from roughly -1.25 to 1.28. The coefficients of Table VI represent the percentage change in country fixed effects following a unit change in the corresponding preference variable. However, all preference variables are reported as scores varying roughly from -1 to 1. Thus, speaking of a unit change in either of these does not make sense. In the discussion and interpretation of the results, we will consistently consider the effects of a $10^{th}$ of a unit change. Following, we will consider the effects of a 0.1 increase in the score of preference $k$, which leads to a $\beta_k/10$ change in the country fixed effects. Furthermore, because the country fixed effects are measured in natural logarithms, this implies an approximate change of $100 \times (\beta_k/10)$ % in a country's time invariant pollution level. Table A-V in the appendix presents a helpful overview of the magnitude and variance of the variables used in this section.

Optimally, we would like to include all preference measures in our model, but it might hurt the efficiency of our estimators. However, for the full model of column 6, all VIFs are below 3 and does not indicate problems of multicollinearity according to this rule of thumb. Thus, we do not have indications of multicollinearity hurting the efficiency of our estimators. However, we see that the estimated effect of positive reciprocity loses some efficiency, but is still significant in the full model. As we do not reject the possibility that all preference variables have a true effect on pollution, we believe excluding variables might lead to omitted variable bias. Thus, as we do not believe there are severe problems of multicollinearity present, we evaluate potential omitted variable biases to be more problematic than the efficiency issue. Our preferred model with inclusion of all explanatory variables, is presented in column 6 of Table VI. We also present a pairwise correlation matrix in Table VII, and pay attention to highly correlated pairs of preference variables.

Table VI
OLS regressions
*Dep. var.:*
*Country effects*

| | **(1)** | **(2)** | **(3)** | **(4)** | (5) | **(6)** |
|---|---|---|---|---|---|---|
| Patience | $-0.713^{***}$ | $-0.704^{***}$ | $-0.854^{***}$ | $-0.924^{***}$ | $-0.878^{***}$ | $-0.891^{***}$ |
| | (-4.20) | (-4.18) | (-5.06) | (-5.49) | (-5.25) | (-5.21) |
| Positive reciprocity | | -0.266 | -0.120 | -0.0115 | -0.383 | -0.416 |
| | | (-1.41) | (-0.64) | (-0.06) | (-1.38) | (-1.44) |
| Negative reciprocity | | | $0.719^{***}$ | $0.683^{***}$ | $0.682^{***}$ | $0.650^{**}$ |
| | | | (2.80) | (2.72) | (2.76) | (2.52) |
| Risk taking | | | | $0.431^{**}$ | $0.358^{*}$ | $0.358^{*}$ |
| | | | | (2.03) | (1.68) | (1.67) |
| Altruism | | | | | $0.482^{*}$ | $0.470^{*}$ |
| | | | | | (1.79) | (1.73) |
| Trust | | | | | | 0.114 |
| | | | | | | (0.46) |
| Constant | 0.00811 | -0.00348 | 0.00818 | 0.000331 | -0.00912 | -0.00677 |
| | (0.12) | (-0.05) | (0.13) | (0.01) | (-0.15) | (-0.11) |
| Breusch-Pagan test | 0.23 | 0.29 | 1.67 | 1.92 | 1.31 | 1.01 |
| | (0.6321) | (0.7476) | (0.1827) | (0.1186) | (0.2703) | (0.4263) |
| *Observations* | 66 | 66 | 66 | 66 | 66 | 66 |
| *Adj. $R^2$* | 0.20 | 0.22 | 0.29 | 0.33 | 0.35 | 0.34 |

Table VI presents the OLS estimators from regressing equation (7). The dependent variable country effects are the individual fixed effects retrieved from the FE-estimation of the World sample using all obs. 1990-2017 (Table IV). Figures in parentheses are t statistics for coefficients and significance levels for Breusch-Pagan test statistics. $H_0$ in Breusch-Pagan test is homoskedastic error terms.
Significance levels: $^{*}$ p < 0.1, $^{**}$ p < 0.05, $^{***}$ p < 0.01

Table VII
Correlation matrix

| | Country effects | Patience | Positive reciprocity | Negative reciprocity | Risk taking | Altruism |
|---|---|---|---|---|---|---|
| Country effects | 1 | | | | | |
| Patience | $-0.465^{***}$ | 1 | | | | |
| Positive reciprocity | -0.171 | 0.0336 | 1 | | | |
| Negative reciprocity | 0.171 | $0.297^{**}$ | $-0.258^{**}$ | 1 | | |
| Risk taking | 0.157 | $0.216^{*}$ | $-0.295^{**}$ | $0.206^{*}$ | 1 | |
| Altruism | 0.0549 | -0.0528 | $0.744^{***}$ | $-0.207^{*}$ | -0.118 | 1 |
| Trust | -0.0441 | $0.243^{**}$ | $0.391^{***}$ | 0.193 | -0.0364 | $0.332^{***}$ |

Table VII shows the pairwise correlation. Country effects are the individual fixed effects retrieved from the FE estimation of the World sample using all obs. 1990-2017 (Table IV).
Significance levels: $^{*}$ p < 0.1, $^{**}$ p < 0.05, $^{***}$ p < 0.01

Our model explains 34% of the variation in country fixed effects, and a Chow-test strongly rejects that none of the preference measures have effects. We find that populations' level of patience, negative reciprocity, risk taking and altruism have significant effects on the country fixed effects of pollution in the 66 countries analysed. All effects are prone to endogeneity issues however. We can therefore only draw conclusions on correlations, and not causality. Discussions on how relationships can go both directions are elaborated in the analysis presented in section 7.

Our first result is that country fixed effects decreases by -0.891 for each unit increase in patience. Thus, a 0.1 score point increase in patience decreases the time invariant pollution by approximately 8.9%. For an average country, this amounts to a decrease of 0.36 $\mu g/m^3$. The effect is statistically significant and the sign of the coefficient is meaningful. When populations are more patient, they depreciate future utility less, and consume less goods and services with negative environmental externalities today. Following this line of thought, countries with more patient populations have lower concentrations of particulate matter. The size of the effect is also rather robust for different model specifications.

Next, if a population's score for negative reciprocity is increased by 0.1, the level of time invariant particulate matter increases by approximately 6.5 % in that country. For the average country, this corresponds to an increase of 0.26 $\mu g/m^3$. The effect is statistically significant and has a positive sign in line with expectations. We believe negative reciprocity and positive reciprocity tells two stories of the classical problem where one only cares as much as you experience others to care. For negative reciprocity, it implies that if your neighbour ignores your desire for clean air in the morning when he takes his car to work, you take revenge of his desire for clean air when you drive to work the next morning. For positive reciprocity, the opposite arguments go; if your colleague rides her bike to work, you are more likely to also ride your bike to work. Thus, the coefficients for both negative and positive reciprocity is in line with expectations. However, of the two, only the effect of negative reciprocity is statistically significant. The coefficient of positive reciprocity might be inefficient due to high correlations with other explanatory variables. Especially, the estimator seems influenced by altruism. We therefore focus on the effect of negative reciprocity, but bear in mind that there could be an opposite effect of positive reciprocity as part of the story.

If a population scores 0.1 point higher on risk taking, the time invariant pollution will increase by approximately 3.6 %, implying an increase of 0.15 μg/$m^3$ for the average country. The effect might work through a hypothesis where risk willing people are more likely to neglect the negative effects of pollution to consume more. The effect is statistically significant only at the 10 % level, but rather robust for different model specifications.

Altruism has a positive effect on pollution of 0.47 % in the preferred model. The effect of altruism is statistically significant at the 10 %-level, but the sign of the coefficient does not support a hypothesis that more altruistic populations will act in ways that improve air quality for the community. However, the relationship might be more complex. All in all, one should be careful in interpreting the effect of altruism as the size and significance of it varies greatly for different model specifications. In example, if we exclude positive reciprocity from the model, the effect of altruism drops significantly to 0.2, and is not statistically significant. Thus, the estimated effect of altruism might be driven by the correlation with positive reciprocity.

Lastly, we have controlled for the effect of trust which is small and statistically not significant. There are indications that there is multicollinearity between altruism and positive reciprocity as they were sensitive to inclusion and exclusion of the other. We can thus not make inference about the effects of these, but including them as control variables are valuable as long as they are not collinear with other variables.

***Main result 4:*** *Countries with higher levels of patience experience less time invariant pollution, while higher levels of negative reciprocity and risk taking is associated with higher levels of* $PM_{2.5}$.

### 6.2.2 Differences in estimated EKC across preferences

In this subsection, we investigate whether preferences can not only affect the time invariant pollution, but also affect the form of the EKC. In order to answer this question, we group countries according to their preference scores and go back to panel estimations. This opens up for the possibility that preferences can impact the effects of economic growth on pollution and thus also the turning points.

In order for us to answer these questions, we split all 66 countries in two groups for all preference measures. Thus, for each preference measure, we have two sub samples of countries – one for countries with higher scores, and one for lower. For simplicity, both in methodology and interpretation of the estimated results, we set the cut-off between the two groups to be zero for all preference variables. This threshold splits the countries into two roughly equally large groups for all five preference variables (see Table III).

We estimate individual EKCs for all ten sub samples, using the fixed and random effects models on equation (1). For each pair of sub samples, we perform a Chow test to conclude whether the pairwise difference in the estimated curves is statistically significant. The relevant estimation results are presented in Table VIII.

Table VIII
Regression results
Negative reciprocity
(log-log)

| *T* | **Falk sample** *N* **= 66** | | **Negative reciprocity > 0** *N* **= 33** | | **Negative reciprocity < 0** *N* **= 33** | |
|---|---|---|---|---|---|---|
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | $0.6636^{***}$ | $0.7011^{***}$ | $0.7652^{***}$ | $0.7942^{***}$ | $0.7375^{***}$ | $0.8704^{***}$ |
| | (5.03) | (4.70) | (4.17) | (3.99) | (5.05) | (5.07) |
| $(\ln GDP/P)^2$ | $-0.0368^{***}$ | $-0.0403^{***}$ | $-0.0407^{***}$ | $-0.0431^{***}$ | $-0.0437^{***}$ | $-0.0566^{***}$ |
| | (-4.94) | (-4.69) | (-4.01) | (-3.82) | (-4.18) | (-5.06) |
| Constant | 0.2896 | 0.2387 | -0.2037 | -0.2682 | 0.0782 | -0.0843 |
| | (0.48) | (0.36) | (-0.24) | (-0.29) | (0.15) | (-0.13) |
| Turning point | 8,236 | 5,994 | 12,094 | 10,031 | 4,620 | 2,184 |
| *p* | $0.754^{***}$ | $0.750^{***}$ | $0.684^{***}$ | $0.684^{***}$ | $0.684^{***}$ | $0.738^{***}$ |
| AR(1) | (24.76) | (24.58) | (16.73) | (16.71) | (16.71) | (16.09) |
| Breusch-Pagan test | $2.92^{*}$ | $2.84^{*}$ | $2.33^{*}$ | 2.18 | 1.89 | 2.20 |
| | (0.0546) | (0.0587) | (0.0990) | (0.1144) | (0.1528) | (0.1346) |
| Wald test | $10{,}726^{***}$ | | $48{,}177^{***}$ | | $21{,}844^{***}$ | |
| | (0.0000) | | (0.0000) | | (0.0000) | |
| Chow *F*-test | $4.14^{**}$ | $9.73^{***}$ | | | | |
| | (0.0204) | (0.0077) | | | | |
| Hausman test | | $21.64^{***}$ | | $10.83^{***}$ | | $28.28^{***}$ |
| | | (0.0000) | | (0.0044) | | (0.0000) |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 792 | 792 | 396 | 396 | 396 | 396 |
| Adjusted. $R^2$ | 0. 3680 | | 0. 3472 | | 0. 4014 | |

Table VIII shows the results from estimating unobserved effects equation (1) for the Falk sample and the two sub samples of higher and lower levels of negative reciprocity over the full sample period 1990-2017. Dependent variable is the level of population weighted mean exposure to $PM_{2.5}$, in country *i* in year *t*, in natural logarithms. Figures in parentheses are *t* statistics for regression coefficients and significance levels for the Breusch-Pagan, Wald, Chow and Hausman test statistics. *t* statistics are calculated based on robust standard errors that allow for within-country correlation. Turning points are in 2011 purchasing power parity international dollars. AR(1) is a t-test on the residual autocorrelation coefficient *p*. $H_0$ in Breusch-Pagan and Wald[1] tests is homoskedastic error terms. $H_0$ in the Chow F-test is that all slope coefficients are equal across classification groups. The null hypothesis of the Hausman test is that RE estimators are unbiased. The Hausman test is performed using covariance matrices based on the estimated disturbance variance from the consistent estimator. Bahrain and Saudi-Arabia are excluded from the Higher SDI sample, and Russia is included in the Lower SDI sample.
Significance levels: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. [1]Within-country homoskedasticity

The analysis finds that countries with higher levels of negative reciprocity experience greater effects on pollution from economic growth than countries with lower levels, as the Chow test rejects equal effect for the income terms for lower and higher negative reciprocity countries. This also implies that these countries reach the turning point later. We cannot conclude on a causal relationship between higher levels of negative reciprocity and the polluting effects of economic growth, but there is a pattern where countries with higher levels also have higher effects of income.

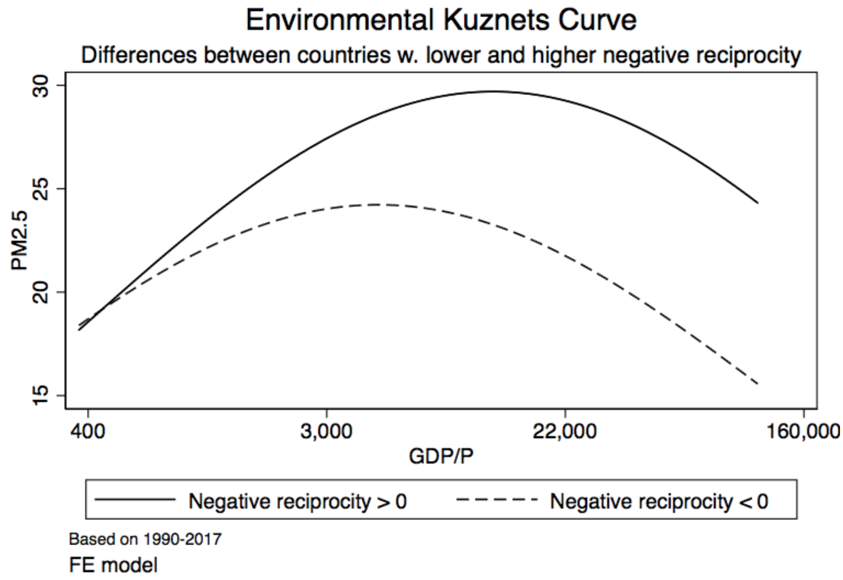
For all other pair of sub samples, the Chow test cannot reject the null hypothesis of equal slope coefficients for lower and higher scores of the other five preference variables. Thus, for other preferences, we do not find evidence that higher or lower levels matter for the form of the EKC.

When performing the Chow test, testing for differences in the estimated slope coefficients (*ln GDP/P* and $ln(GDP/P)^2$) between two sub samples, all countries are assumed to follow the same time trend. This might not be true of course. However, it is only for the sub samples of higher and lower risk taking we find evidence for different time trends through a joint significance test of the sub sample individual time effects. If we allow for different time trends for these sub samples, the Chow test still cannot reject equal EKCs however.

The estimated EKCs for the two sub samples on negative reciprocity is presented in Table VIII. The estimated coefficients of *ln(GDP/P)* are 0.7652 and 0.7375 for countries with negative reciprocity scores above and below zero respectively. For the squared term, $(\ln GDP/P)^2$, the estimated coefficients are -0.0407 and -0. 0437 for the same groups. The Hausman test rejects equal estimators for the FE and RE models for the pooled sample and both sub samples. Estimators from all three RE models are thus biased, and the preferred models are the three FE models.

The two Environmental Kuznets Curves for countries with higher and lower negative reciprocity are illustrated in Figure VIII. The solid line is the estimated EKC for countries with higher levels of negative reciprocity in the population, while the dashed line is the estimated curve for countries with lower levels of negative reciprocity. Notice that the vertical axis showing economic development is exponential.

Figure VIII




Estimated EKCs for the sub samples of countries with higher and lower negative reciprocity. Curves are estimated based on the fixed effects model in log-log, but illustrated in level-level. Notice that the horizontal axis is exponential and ticks approximate. See table VIII.

As seen from Figure VIII the estimated EKC for countries with higher negative reciprocity is steeper in incline, but reaches the turning point later than the estimated EKC for countries with higher negative reciprocity. Initially, economic development has a greater increasing effect on pollution in countries with higher levels of negative reciprocity in early stages. This supports the hypothesis proposed in the previous subsection, that more negatively reciprocated individuals care less about air quality when others do neither. Thus in an economy with polluting goods and services, there will be air quality depletion.

Countries with lower levels of negative reciprocity also reach the turning point at a later stage of economic growth. Countries with lower levels of negative reciprocity reach the turning point at $4,260 GDP per capita, almost two thirds less than countries with higher levels of negative reciprocity at $12,094. As the incline in the estimated EKC for countries of higher negative reciprocity is both steeper and longer lasting, the average country in this group also experiences higher levels of particulate matter before reaching the turning point. Thus, we see that rather small differences in the estimated effects of economic development yield large differences in turning points.

***Main result 5:*** *Countries with higher levels of negative reciprocity experience greater effects on pollution from economic growth than countries with lower levels, and reach the turning point later.*

### 6.2.3 Back-of-the-envelope calculations on the effects of preferences

In this subsection, we present back-of-the-envelope calculations to illustrate the estimated effects of preferences on a specific country's estimated EKC. First, we highlight Italy to illustrate preferences' effects on the time invariant pollution levels, and what implications this may have for Italy's total pollution levels. Secondly, we highlight Tanzania to illustrate the matter of negative reciprocity for their estimated EKC path, and the implications of higher negative reciprocity going forward.

#### *6.2.3.1 Effects of preferences on time invariant pollution in the example of Italy*

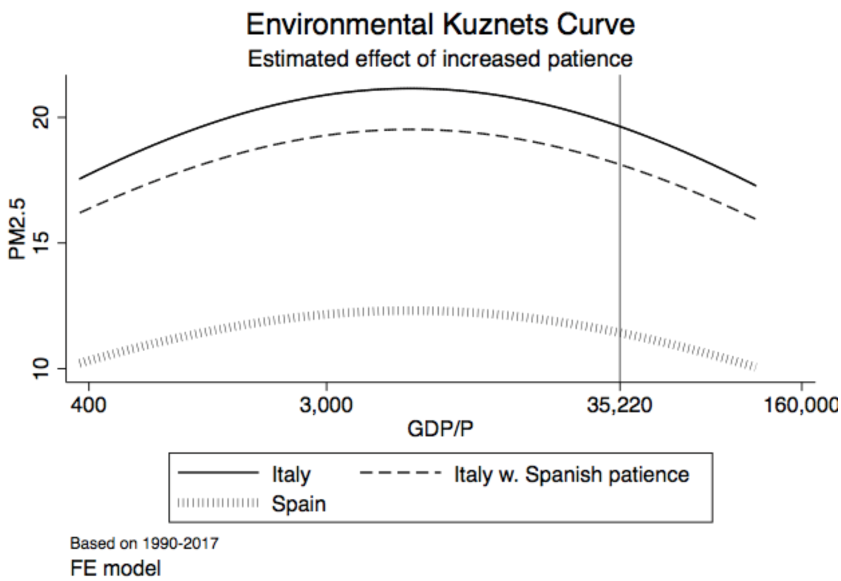
In the first subsection on preferences, we found that patience, negative reciprocity, risk taking and altruism have statistically significant effects on country fixed effects of pollution. We also remember however that we were especially cautious in interpreting the effects of altruism. Because patience seemed to be the preference variable with the greatest and most stable effect, we will elaborate how changes in level of patience affect the estimated EKC of a given country.

Because we assume preferences to be constant over time, patience does only affect the intercept of the EKC in this scope of the analysis, namely the country fixed effects. A change in patience will thus only lead to a parallel vertical shift in the curve, and not change the slope. This parallel shift corresponds to the change in the time invariant pollution levels – the country fixed effects.

To illustrate, we highlight Italy, which population scores rather low on patience with a score of approximately 0.11. In 2017, Italy had a gross national product per capita amounting to \$35,220, and a mean $PM_{2.5}$ exposure of 17 μg/m$^3$. For comparison, we also highlight Spain. Across the Mediterranean for Italy, the Spanish population is slightly more patient with a score of approximately 0.20. Thus, the Spaniards score almost 0.1 points higher in patience than their Italian friends. The effect of this difference in patience on country fixed $PM_{2.5}$ exposure, is estimated in section 1 to be approximately 8.9 %. Thus, if Italians had, and had always had, the same level of patience as the Spaniards, the intercept of their estimated EKC would be 8.9% lower, all else equal. Following, for all levels of economic development, Italians would experience 8.9 % lower pollution levels. This implies a mean level of $PM_{2.5}$ at 15.47 μg/m$^3$ in 2017, 1.53 μg/m$^3$ less than the true value.

The isolated effect of patience on country fixed pollution is illustrated in Figure IX below, by the example of Italy. The solid line is Italy's estimated EKC from the World FE model from subsection 6.1.1, and dotted line is Spain's estimated EKC from the same model. The dashed line is Italy's estimated curve if they had had the same patience level as the Spanish population, all else equal. The vertical line indicates Italy's level of economic development in 2017. $PM_{2.5}$ on vertical and GDP per capita on horizontal axis are in levels, but the vertical axis showing economic development is exponential.

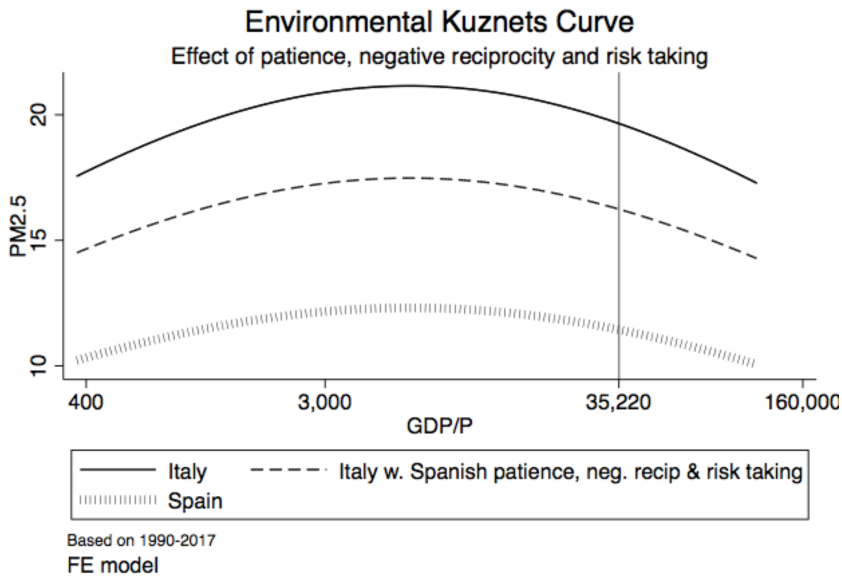
Figure IX




Estimated EKC for the Italy and Spain. Slope and country fixed effects retrieved from FE estimation on World sample (Table IV, col. 1). Curves are estimated in log-log, but illustrated in level-level. Notice that the horizontal axis is exponential. Vertical line indicates Italy's level of GDP/P as of 2017. The shift from solid to dashed curve is parallel in log-log. See Table IV and VI.

From Figure IX we observe that the estimated EKC of Italy shifts towards the curve for Spain. There is still a substantial difference in the levels of the curves, which explanation lies in differences in other constant characteristics of the countries. We could go one, and even two, steps further and also take differences in negative reciprocity and risk taking into account. Italians are both more willing to take revenge and risk. Following the same line of arguments and assumptions as for preferences, Italy's levels of $PM_{2.5}$ exposure would be approximately 2.3[11] % and 8.7[12] % lower respectively, if their population had the same levels of negative reciprocity and risk willingness as the Spaniards. Adjusting these preferences for Italy brings the estimated EKC closer to the parallel[13] EKC of Spain, as shown in Figure X.

Figure X




Estimated EKC for Italy and Spain. Slope and country fixed effects retrieved from FE estimation on World sample (Table IV, col. 1). Curves are estimated in log-log, but illustrated in level-level. Notice that the horizontal axis is exponential with approximate values at tics. See table IV and VI. Vertical line indicates Italy's level of GDP/P as of 2017.

[11] $(0.18 - 0.311) \times 0.65$

[12] $(-0.09 - (-0.16)) \times 0.358$

[13] The curves are parallel in their estimated functional form, log-log.

We see that there is still a difference between the two modified EKCs of Italy and the EKC of Spain, implying that there are other differences in constant attributes of the two countries that has an effect on particulate matter. However, these back-of-the envelope calculations illustrate that preferences can explain a substantial amount of the differences in the country fixed $PM_{2.5}$ exposure. Differences in patience, negative reciprocity and risk taking are together able to explain approximately 35 % of the difference in country fixed effects between Italy and Spain.

#### *6.2.3.1 Effects of negative reciprocity on estimated EKC in the example of Tanzania*

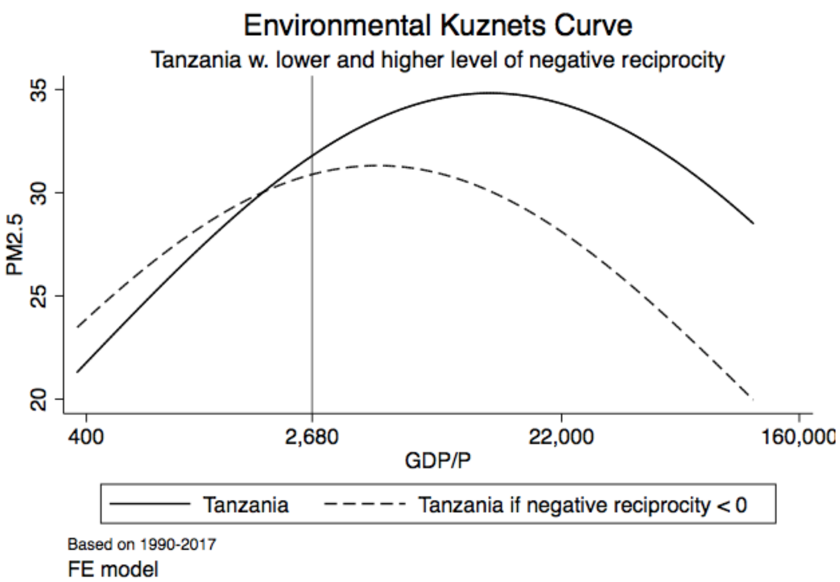
In 6.2.2, we found that countries with higher levels of negative reciprocity experience a steeper and longer way to the turning point of the EKC. Both prior to the turning point and after, economic growth has greater effects on pollution in countries with higher levels of negative reciprocity. In this section, we seek to illustrate the differences for a given country, here being Tanzania. Tanzania is chosen as they have a slightly positive level of negative reciprocity (0.05) and is yet to reach the estimated turning points of both models, with a gross national product per capita in 2017 at $2,683. Thus, if they would have had slightly lower levels of negative reciprocity, they would be estimated to follow an EKC which would make predict them to reach the turning point sooner, and limiting the temporary increase in pollution along the way.

Because one cannot make inference about the results from the fixed effects method out of sample, we cannot say if Tanzania would have had negative levels of negative reciprocity, they would follow the EKC of the sub sample of lower negative reciprocity countries estimated in Table VIII. Thus, we give Tanzania a score of negative reciprocity below zero (and for this illustration it does not matter how much below), and move them from the sub sample of countries with higher negative reciprocity to the sub sample of lower negative reciprocity.

We estimate new EKCs using the fixed effects model on the modified sub samples. Performing Chow tests tells us that including Tanzania in the lower negative reciprocity sub sample has statistically significant effects on the estimated EKC for this group, but they also tell that there is still a significant difference between the two groups. Furthermore, the pattern remains as all coefficients of the income terms change in the same direction. Countries with higher levels of negative reciprocity still experience a greater and longer lasting increase in pollution along economic growth. We present the numerical results of this in appendix B.

The implied consequences for Tanzania, of having a lower level of negative reciprocity in the population is illustrated in Figure XI below. The solid line is the estimated curve for countries with higher levels of negative reciprocity, with the specific intercept of Tanzania. The dashed line is the estimated EKC for Tanzania if they had scored below zero on negative reciprocity, all else equal. The vertical line indicates the level of GDP per capita in Tanzania per 2017. Curves are estimated in log-log, but illustrated in levels. Notice that the vertical axis showing economic development is exponential.

Figure XI




Estimated EKCs for Tanzania where the difference in estimates is caused by level of negative reciprocity. Illustration based on models in col 3 and 5[1] of table VIII. Curves are estimated in log-log, but illustrated in level-level. Notice that the horizontal axis is exponential with approximate values at tics. Vertical line indicates Tanzania's level of GDP/P as of 2017.

[1] Model in illustration slightly different due to including Tanzania in estimation. See the model used in appendix B-II

Figure XI explicitly illustrates the differences in the estimated EKC of Tanzania depending on their level of negative reciprocity. Remember that the dashed line is a hypothesized line, which should be interpreted as the EKC for Tanzania if they had, and had always had, a lower level of negative reciprocity. Still in the zone where economic growth is seen with increased pollution levels, the differences in paths is significant. In a world where the Tanzanian people had been less negative reciprocated, they would be estimated to reach the turning point at a level of GDP per capita of \$4,682, which is \$7,412 less than the estimate based on their true level of negative reciprocity. Furthermore, they would limit pollution on their way there. At \$4,682 GDP per capita, they are estimated to be exposed to $PM_{2.5}$ at a level of 33.6 $\mu g/m^3$. The levels are also estimated to increase more reaching 34.9 $\mu g/m^3$ at the most. At the same time, the estimated path if they would have had lower levels of negative reciprocity, peaks at 31.2 $\mu g/m^3$. Thus, the informal calculations illustrate how negative reciprocity may not only affect the positioning of the estimated EKC in the vertical landscape, but also the form of it. Exemplified by Tanzania, we see how levels of negative reciprocity can affect both turning points and levels of exposure experienced along the way.

## 6.3 Diff-in-diff results

Table IX shows the results of estimating the effect of the Directive 50 on $PM_{2.5}$ in EU countries using a difference-in-difference estimation technique. Columns 1 through 3 shows the results from estimating the effect of Directive 50 when comparing to all other countries in the sample. Columns 4 through 6 shows the results for estimating the effect of Directive 50 on the subset of developed countries. To account for the effect of economic development we have included income terms in columns 2, 3, 5 and 6. This allows us to assess the effect of Directive 50 independent of changes in income.

TABLE IX
Difference in difference
EU Directive 50 2008
1990-2017

| Comparison group | **World** $N = 157$ | | | **Higher SDI countries** $N = 82$ | | |
|---|---|---|---|---|---|---|
| Model | Col 1 | Col 2 | Col 3 | Col 4 | Col 5 | Col 6 |
| EU | -0.675*** | -0.661*** | -0.627*** | -0.475*** | -0.455*** | -0.455*** |
| | (-7.55) | (-7.15) | (-6.93) | (-4.69) | (-4.50) | (-4.49) |
| Post 2008 | -0.118*** | -0.1114*** | -0.110*** | -0.173*** | -0.161*** | -0.161*** |
| | (-10.57) | (-9.70) | (-9.64) | (-9.66) | (-8.62) | (-8.71) |
| EU post 2008 | -0.0755*** | -0.0765*** | -0.0620*** | -0.0617*** | -0.0647*** | -0.0644*** |
| | (-9.75) | (-9.87) | (-7.00) | (-6.09) | (-6.36) | (-5.58) |
| Constant | 3.326*** | 3.393*** | 2.012*** | 3.127*** | 3.346*** | 3.296*** |
| | (73.20) | (30.96) | (5.13) | (47.78) | (14.36) | (3.03) |
| $R^2$ | 0.1904 | 0.1990 | 0.2098 | 0.2068 | 0.2185 | 0.2189 |
| Observations | 1884 | 1884 | 1884 | 984 | 984 | 984 |
| Control variables: | | | | | | |
| log GDP/P | No | -0.00797 | 0.3186*** | No | -0.0234 | -0.0126 |
| | | (-0.67) | (3.59) | | (-1.02) | (-0.06) |
| (log GDP/P)$^2$ | No | No | -0.0190*** | No | No | -0.0006 |
| | | | (-3.77) | | | (-0.05) |
| Time-fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |

Table IX shows the regression results of the from difference-in-difference method (DiD). The dependent variable is log $PM_{2.5}$ exposure. Columns 1-3 compare the EU countries for which the regulation affects to all other countries in our world sample, while column 4-6 compare to all Higher SDI countries. All 21 EU/EEA countries are part of the sub sample Higher SDI countries. The DiD-estimator is “EU post 2008”. The constant is the average level of $PM_{2.5}$ exposure in the world (col 1-3) and higher SDI countries (col 4-6). EU is the difference in intercepts between the EU countries and the comparison group. Post 2008 is the joint slope coefficient of EU countries and the comparison group before the policy introduction. While the comparison group follow this slope also after the policy introduction, the slope of EU countries also takes in the DiD-estimator -EU post 2008 - which is the effect of the policy. The slope of the EU countries after introduction of the regulation is thus Post 2008 + EU post 2008. See Figure XII for illustration of Table IX. Figures in parentheses are *t* statistics calculated based on robust standard errors clustered on countries. Bahrain and Saudi Arabia are *not* excluded from Higher SDI countries. Significance levels: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The coefficient *EU* captures the average difference between EU countries and non-EU countries existing before the introduction of the directive. We see that EU countries had significantly lower emission than countries outside of the EU. This effect is significant in the full sample and when comparing EU-countries to other developed countries. Compared to the world sample the EU-countries have 45% lower $PM_{2.5}$ levels[14]. When estimating using the sample of developed countries, EU-countries have about 35 % lower pollution levels than other developed countries. We also see that there is a significant negative effect on pollution after 2008. For the entire sample, we see that post 2008 $PM_{2.5}$ levels are 10.4% lower than before 2008. The effect is greater for developed countries where pollution levels are about 14.9 % lower after 2008.

For both the full sample and the sub sample of developed countries however, pollution in EU countries decreases significantly more after 2008. The EU post 2008-term captures the effect of a country being an EU member after 2008. This is the term of interest as it captures the possible effect of the implementation of Directive 50. The estimated effect of is about 6 % and is significant at the 1 %-level. This suggests that the regulation implemented in 2008 has had an effect on the level of $PM_{2.5}$ pollution.

***Main result 6:*** *Implementing Directive 50 in the EU had a significant negative effect on $PM_{2.5}$ pollution in member states.*

Including the EKC relationship in the estimation has little effect on the estimated coefficients. The estimated coefficients change little when including the two income terms. Neither does it affect the significance of the results. The $R^2$ increases slightly when including the EKC-relation. When including income terms in the estimation of the full sample we find the same relation between economic development and $PM_{2.5}$ exposure as in Table IV. The linear income term is positive, and the squared term is negative. When looking only at developed countries

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[14] Do note that because there are relatively large coefficients, and thus the approximate interpretation that a unit change in the explanatory $x_k$ leads to a $100 \times \beta_k\%$ change in the dependent variable is too unprecise. Thus, for relatively large coefficients we use the exact percentage effect given by; $100 \times (\exp(\beta_k) - 1)$.

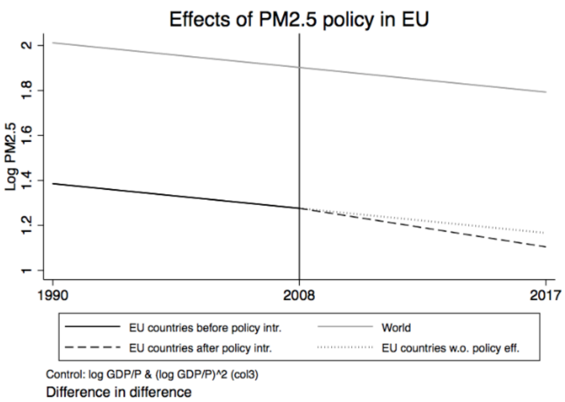
we find that the GDP terms are not significant. This is the same relation as we found in Table IV. We prefer to include the income terms however, as the presence of a World EKC indicates that there is a true relationship between economic growth and pollution.

Figure XII illustrates the estimations from columns 3 and 6. The vertical line indicates the introduction of Directive 50. The solid grey line shows the continuous trend of $PM_{2.5}$ exposure in non-EU countries. The solid black line shows the trend in EU countries over the whole period. We see that before 2008 the EU had significantly lower emission compared to both the world sample and the high-SDI sample.

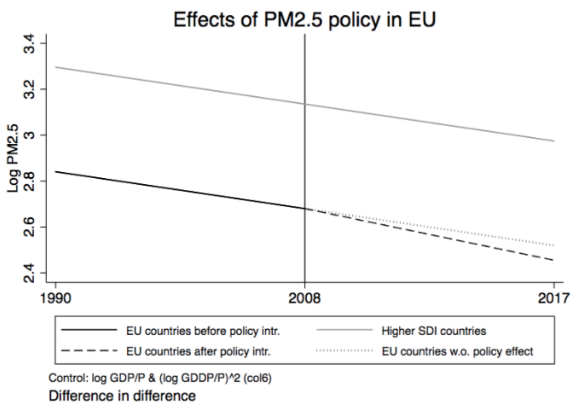
The dashed black line is the trend in EU countries after the implementation, while the dotted line is an extension of pre-2008 trend in EU countries. The latter is thus a hypothesized path for EU countries had the regulation not been implemented. Following, the effect of the regulation on $PM_{2.5}$ exposure in EU countries is illustrated by the difference between the black dashed line and the dotted line. We see that, due to the regulation, the decline in $PM_{2.5}$ exposure after 2008 is steeper for EU countries than for non-EU countries.

Figure XII
Difference-in-Difference

**World**




**Higher SDI countries**




See table IX for regression results and model specifications.

# 7. Analysis

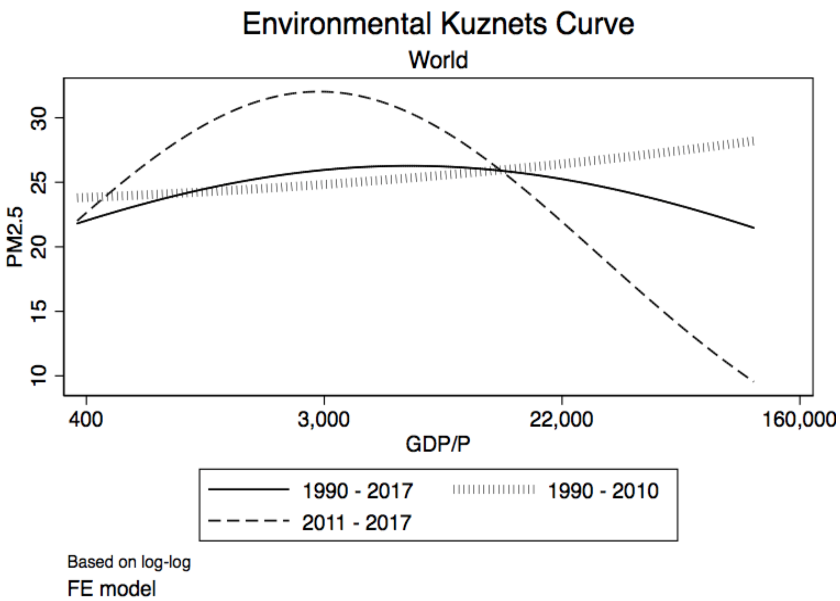
In the following sections, we analyse and explain the results presented in chapter 6. The reasoning and explanations are based both on comparisons to existing literature and economic intuition.

## 7.1 EKC-analysis

From estimating the EKC in section 6.1 we have two insights. There seems to be a World EKC which have shifted and is steeper in the period 2011-2017 than in the period as a whole.

A World EKC implies that developed and developing countries move along the curve in the same way. One way to understand this is to analyse the empirical relationship using the insights from (Pecchenino, 1994). In this model a country chooses between investing in a consumption good or an abatement good. For a world EKC to be present then firms should have access to the same set of production technology but have different levels of capital which translates into different levels of income. We can interpret countries decision in the following way: If a country is to the left of the turning point prefer it prefers to consume more over investing in abatement good. The opposite if countries are to the right of the turning point. Our estimated turning point is $2,860 for 2011-2017, which is lower than for the period as a whole of $6,015.

Figure IX




World EKCs from the fixed effects model based on different time periods. Estimation based on log-log model, but here illustrated in levels. See Table V. Note that the time effects are excluded. Horizontal axis is exponential and ticks are approximate.

There are several possible reasons for why the EKC has changed shape over time. One possible reason is reduced costs of technology. Since the curvature is steeper this could be an indication that technology is implemented earlier in the developing cycle. If poor countries can gain access to cars and fossil fuel-based power generation for example, this should make countries grow faster but with more pollution. If also abatement technology has become cheaper over the period this should allow countries to adopt cleaner technologies earlier, and reach the turning point earlier, as a cleaner environment is relatively cheaper.

Another possible reason for the steeper decline in pollution is that research has revealed $PM_{2.5}$ to be more dangerous than previously believed (WHO, 2003). Increased knowledge and awareness about the health risks of $PM_{2.5}$ should make policymakers respond by implementing stronger regulations. We see several countries passing or strengthening regulation in the period. The EU passed comprehensive regulations in 2008 (EU, 2008). The US strengthened its regulation in 2012 (EPA, 2012) and China passed comprehensive air quality reform in 2013 (Zhang, 2018). This indicates that several countries are concerned about the impact of $PM_{2.5}$. With more comprehensive regulations countries' pollution levels should decline more rapidly.

This effect should be stronger in democratic countries. Assuming individuals to have preferences for a cleaner environment, voters should prefer candidates who enforce stricter regulation of pollutants. As there has been increased democratization over the last decades (IIDEA, 2017), this effect should be stronger today.

## 7.2 Analysing the relationship between preferences and $PM_{2.5}$ pollution

This section presents discussions of the estimated relationships between preferences and pollution. Using basic econometric methods, we find significant correlations between time invariant pollution levels and patience, risk taking, negative reciprocity and altruism. We also find that the effects of economic growth are significantly higher in countries with higher levels of negative reciprocity. Though our results are prone to possible endogeneity issues, the results point out interesting correlations and raise questions for further research.

Preferences are affected by exogenous country characteristics such as geography, climate, ethnic diversity and religion (Falk, et al., 2018). According to Falk's estimates, 53% of the variance in preferences across countries can be explained by these characteristics. The same numbers for risk taking and altruism are around 25 %. Generally, "preferences are spatially and culturally correlated" (Falk 2015). Western-European countries tend to be more patient and negative reciprocated. Eastern Europe and East and South Asia are on average more risk averse and less patient. South Americans tend to be more impatient and less negative reciprocated. Thus, if we believe one or more of these characteristics to have an effect also on pollution levels, our estimate of patience's effect on pollution is biased due to omitting these variables. While it seems questionable if ethnic diversity and religion have true effects on pollution, it seems reasonable that there are true effects of geographical and climatic variables as $PM_{2.5}$ has both man-made and natural sources. Thus, we should be aware that our estimated effects of preferences on pollution might be biased. As patience is generally the most correlated preference, we suspect it's effect to be biased.

Due to these possible endogeneity issues, we cannot make causal claims but the relationships between preferences and pollution still seem relevant. The estimated results support different hypothesised mechanisms between individual behaviour and aggregate pollution levels. Though the relationships might work both ways, we believe preferences have effects on pollution both through daily decisions and through life choices and accumulation processes of individuals and institutions.

A lot of economic theory and research include patience and risk taking to explain both short and long term decisions that affect a range of economic outcomes which in turn affect the environment. We thus believe patience and risk taking to have true effects on time invariant pollution. In a micro perspective, we believe it has effects on individual consumption as impatient individuals discount future utility relatively less. Thus, in an economy where pollution is a negative externality of consumed goods and services, patient individuals will pollute less through decreased consumption today. This can be supported by the correlation between saving decisions and patience in Falk et.al. (2018).

Furthermore, we believe patience to work the same ways through accumulation decisions and life choices. Falk et.al. (2018) find that more patient populations have higher levels of education. Thus patience might affect pollution through increased information and knowledge. Education and awareness are two underlying determinants that Stern (2004) argues have an effect on environmental quality through proximate mechanisms such as economic structures, product and input mixes, technology and scale.

Patience is also correlated with the degree of institutional development (Falk, et al., 2018). Thus, more patient populations experience higher air quality as there are stronger institutions to limit pollution and incentivise abatement in these countries. In markets with negative externalities there is a need for market intervention to avoid market failure such as harmful levels of pollution.

In 6.2.1 we argued that negative reciprocity might be an indicator of individuals' lack of will to put more effort into abatement than others. The implications would be that people abate if it increases their own utility, and care less about the wellbeing of others. Consequently, in countries with populations with higher degrees of negative reciprocity one would expect to see more pollution. Thus, if this is true, one would assume negative correlations between negative reciprocity and altruistic behaviour. There are indications of negative relationships between negative reciprocity and altruistic actions, such as donating money, volunteering and helping strangers, though none of these are statistically significant (Falk, et al., 2018).

The positive effect of risk taking on pollution can be seen in light of the ongoing debate about climate risk from an environmental perspective. One side of the climate risk is policy risk, which should be transferable to air pollution. If populations are more risk willing, individuals and enterprises are more likely to ignore these risks. Furthermore, individuals might also be more willing to ignore the negative effects of $PM_{2.5}$ in their decision making.

For all preference variables, causality might go the other way, by pollution levels forming preferences. Ambient levels of $PM_{2.5}$ have proven negative health effects which over time might reduce populations average accumulation of knowledge and awareness. Even more, this discussion raises questions of causality between preferences and proximate mechanisms. It seems hard to find measurable variables that are truly exogenous except geographic and climate. Most likely, preferences, institutions, and cultures coevolve and it is hard to find the causal effects of either one of them.

## 7.3 Difference-in-difference

For the difference-in-difference estimation to identify the effect of the implementation of Directive 50 there are two main assumptions. Firstly the trends of the two groups need to be parallel. If this is not true we cannot be sure whether it is the effect of the implemented law we capture or the different trends of EU-countries and other countries developing over time. The second condition that needs to be satisfied is no anticipation. To make sure we are picking up the effect of the implemented regulation we need to make sure that none of the EU-countries pre-emptively changed their behaviour. If this was the case we cannot describe the full effect of Directive 50.

We found evidence for an EKC for $PM_{2.5}$ in section 6.1. This implies that there is a relationship between income and pollution levels, which is the same for all countries. Therefore we control for income effects, to isolate the general trends in pollution. Evidence for a World EKC implies that these controls should pick up income effects equally good for developed and developing countries, and strengthen the isolating effect. The post-2008 term is highly significant and changes little when including income terms. From this we can be reasonably sure that the trend for the EU is the same as for the control samples.

If there were non-EU countries implementing $PM_{2.5}$ regulations at the same time, this would bias the estimator of the isolated effect. Likewise, the estimator would be biased if there were EU-countries not complying to the Directive. There are some countries that have passed regulations after 2008. This biases the estimated effect of Directive 50 negatively, but since the control sample is large and only some countries have passed regulations this should be dampened by most countries not implementing regulations. All in all we believe that the assumption of parallel trends is satisfied, even though there may be problems with negative bias.

There are several reasons for why we believe that the no anticipation assumption holds. Firstly, it is likely that the salience among the public that the EU had plans to regulate $PM_{2.5}$ pollution was low. The legislative process in the EU is complicated and unless the proposed regulations directly impact businesses it is unlikely that many people are aware of the proposed changes. Furthermore, if we assume the public was aware of the proposed directive it is unlikely that they would change their behaviour in advance. For both business and individuals changing behaviour is costly. $PM_{2.5}$ has a wide range of sources from heating, driving and industrial activity, so the pollution levels are dependent on a range of sources. If there is an anticipation effect in one of the sources, the total effect will still be limited. For example, driving causes $PM_{2.5}$ pollution but individual drivers are unlikely to drive less based on knowledge of a coming EU directive as the possible benefit of implementing change early would have to be greater than the cost of changing behaviour early. This is unlikely to be the case.

The directive requires each member state to institute measures they deem adequate to comply with the goals set by the directive. This makes it more difficult for firms to pre-emptively comply with coming regulation as firms in each country have to follow the legislative process in the EU but also pay close attention to the process to their home country to comply with future laws. For firms the production processes are inflexible in the short run, meaning it is unlikely that they will make changes unless they are legally required to do so. Even more, as our latest observation prior to the implementation is from 2005, it seems less likely that observations of pollution are affected by anticipation. Therefore, we can say that it is reasonable to assume that the no anticipation assumption holds as it would be unreasonable to expect firms and individuals to follow and act based on a complicated legislative process.

Based on our deliberation we can say with a reasonable degree of certainty that the two assumptions using difference-in-difference are satisfied. One thing to note is that when estimating the effect of the directive the closest observations are in 2005 and 2010, meaning we are estimating the effect of the directive based on observations three and two years removed from the implementation in 2008. This can have influenced the magnitude of the estimated effect, as the general trends might have had structural breaks around that time for other reasons than anticipation. However, since we are still comparing effects that are reasonably close to and after the implementation we still believe that we are capturing the effect of the directive. In the estimation both when comparing to the full sample and a sub-sample of developed countries the effect of Directive 50 is about 6 % reduction in pollution.

Therefore, we can say that implementing regulations in the EU had a negative effect on $PM_{2.5}$ pollution. For policymakers, this result should be heartening that, as it shows that, regulatory action can be an important tool to affect change in the fight for cleaner air.

# 8. Conclusion

In this thesis we have explored the relationship between particulate matter pollution and income. We have found evidence that there is an EKC for $PM_{2.5}$. Furthermore we cannot find evidence that the relationship between income and pollution is different for developed and developing countries. This implies that there is a single World EKC.

We find that there is a structural break in time and that the estimated curve has shifted over the years. A "new" EKC based on 2011-2017 shows that pollution is more sensitive to changes in income than for the period as a whole. The estimated turning point for the full sample EKC is \$6,015 while the "new" turning point is \$2,860. This is most likely due to declining costs of technology and increased salience about the health hazards of $PM_{2.5}$ pollution. The country invariant time effect is also increasing in the sample, especially after 2010. This indicates that in general better technology has been adopted, and more so for developed countries. We find evidence of income and pollution to co-integrate. However, we cannot reject non-stationary residuals and these results may be caused by spurious correlations.

Economic preferences may explain some of the estimated country fixed effect from the EKC estimation. Through multiple regression analysis, we found that patience has significant negative correlations with country specific time invariant levels of $PM_{2.5}$ pollution, while negative reciprocity and risk taking have significant positive correlations. Risk taking is also seen with greater impacts on pollution from economic growth, where countries with higher levels of negative reciprocity follow a steeper EKC.

We need to be careful interpreting the results as the estimated EKCs does not represent a causal impact of income on pollution. Income measured in GDP per capita is only a proxy for many different processes that cause $PM_{2.5}$ pollution. Our findings represent interesting correlations between $PM_{2.5}$ pollution, income and preferences.

The evidence of a single World EKC for $PM_{2.5}$ can be an indication that economic growth is not synonymous with environmental degradation. However, for countries struggling with harmful pollution levels there is still the need for regulations as we cannot establish a causal relationship between income and pollution.

The implementation of Directive 50 in the EU had a significant negative effect on pollution levels in member countries. We believe that the difference-in-difference estimator successfully identifies the effect of Directive 50 as the no anticipation and the parallel trend assumptions are satisfied. The effect of the directive is a 6 % reduction both when comparing to the full sample and the sample of developed countries. The effect is robust to inclusion of an EKC-relationship.

Directive 50 is likely to have had a causal impact on pollution because the difference-in-difference assumptions are satisfied. These results indicate that policies and regulations can work. While our analysis captures the average effect for the EU countries as a whole, more work could be done in analysing effects in specific countries. The effect might differ across countries, and such analysis would add to the findings of this thesis.

In the future more research can be done on the relationship between preferences and $PM_{2.5}$ pollution. The type of data we obtain from Falk et. al. (2018) is still relatively scarce, and more research within this field will help extend the possibilities to investigate relationships between individual behaviour and pollution. With more observations over a period of time, we could draw more robust conclusions, and more interestingly investigate the relationships with preference changes over time.

# Appendices

## Appendix A

Table A-I
Regression results
1990-2017
(lin-log)

| Region | **World** <br> ***N* = 157** | | **Higher SDI** <br> ***N* = 77** | | **Lower SDI** <br> ***N* = 78** | |
|---|---|---|---|---|---|---|
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | 6.5728$^{*}$ | 6.8782$^{**}$ | -2.3873 | -1.2752 | 9.1563$^{*}$ | 8.5510 |
| | (1.97) | (2.03) | (-0.49) | (-0.26) | (1.67) | (1.60) |
| (ln GDP/P)$^2$ | -0.3934$^{**}$ | -0.4358$^{**}$ | 0.1084 | 0.0342 | -0.5509$^{*}$ | -0.5182 |
| | (-2.10) | (-2.31) | (0.42) | (0.13) | (-1.70) | (-1.63) |
| Constant | 2.6861 | 3.2915 | 30.5702 | -1.1372 | 2.3104 | 1.5779 |
| | (0.18) | (0.22) | (1.30) | (-0.05) | (4.83) | (0.07) |
| Turning point | 4,246 | 2,674 | 60,569(-) | 124.9’’(-) | 4,056 | 3,830 |
| *p* | 0.705$^{***}$ | 0.606$^{***}$ | 0.658$^{***}$ | 0.658$^{***}$ | 0.612$^{***}$ | 0.612$^{***}$ |
| AR(1) | (35.92) | (30.30) | (23.76) | (22.13) | (21.75) | (21.74) |
| Breusch-Pagan | 3.42$^{**}$ | 25.95$^{***}$ | 3.43$^{**}$ | 3.58$^{**}$ | 1.26 | 1.23 |
| test | (0.0330) | (0.0000) | (0.0326) | (0.0283) | (0.2848) | (0.2938) |
| Wald test | 0.11’’$^{***}$ | | 1.2’’$^{***}$ | | 81873$^{***}$ | |
| | (0.0000) | | (0.000) | | (0.0000) | |
| Chow *F*-test | 0.68 | 2.38 | | | | |
| | (0.5065) | (0.3040) | | | | |
| Hausman test | | 20.90$^{***}$ | | 19.80$^{***}$ | | 2.19 |
| | | (0.0000) | | (0.0001) | | (0.3343) |
| Observations | 1884 | 1884 | 924 | 924 | 936 | 936 |
| Adjusted. $R^2$ | 0.1082 | | 0.5113 | | 0.0695 | |

Table A-I presents the equivalent to Table IV in lin-log form. The dependent variable is population weighted $PM_{2.5}$ exposure in country *i* in year *t* in absolute levels. Figures in parentheses are *t* statistics for regression coefficients and significance levels for the test statistics. *t* statistics are calculated based on clustered standard errors. Signs of income terms are in line with results in Table IV and turning points are reasonable. Thus, these results indicate robustness to the EKC relationship found with the log-log model and elaborated in this thesis. Significance levels: $^{*}$ p < 0.1, $^{**}$ p < 0.05, $^{***}$ p < 0.01.

Table A-II
Regression results
1990-2017
(lin-lin)

| Region | **World** **$N$ = 157** | | **Higher SDI** **$N$ = 77** | | **Lower SDI** **$N$ = 78** | |
|---|---|---|---|---|---|---|
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| GDP/P (000s) | -0.0956$^{**}$ (-1.99) | -0.1400$^{***}$ (-3.46) | -0.0028 (-0.06) | -0.0414 (-0.92) | 0.3374$^{*}$ (1.81) | 0.3117$^{*}$ (1.66) |
| $(GDP/P)^2$ (000s) | 0.0006$^{*}$ (1.69) | 0.0009$^{***}$ (2.83) | 0.0000 (0.07) | 0.0003 (0.79) | -0.0139$^{***}$ (-2.81) | -0.0131$^{***}$ (-2.62) |
| Constant | 30.43$^{***}$ (72.82) | 30.84$^{***}$ (22.01) | 21.56$^{***}$ (29.31) | 22.14$^{***}$ (18.08) | 35.62$^{***}$ (56.11) | 35.69$^{***}$ (17.35) |
| Turning point | (-) | (-) | (-) | (-) | 186,594 | 184,601 |
| *p* AR(1) | 0.608$^{***}$ (30.39) | 0.606$^{***}$ (30.30) | 0.673$^{***}$ (24.39) | 0.667$^{***}$ (24.19) | 0.614$^{***}$ (21.74) | 0.614$^{***}$ (21.72) |
| Breusch-Pagan test | 19.95$^{**}$ (0.0000) | 18.10$^{***}$ (0.0000) | 3.68$^{**}$ (0.0256) | 3.75$^{**}$ (0.0238) | 0.87 (0.4180) | 0.86 (0.4221) |
| Wald test | 0.12’’$^{***}$ (0.0000) | | 0.97’’$^{***}$ (0.000) | | 81101$^{***}$ (0.0000) | |
| Chow *F*-test | 0.21 (0.8108) | 1.71 (0.4245) | | | | |
| Hausman test | | 16.13$^{***}$ (0.0003) | | 25.09$^{***}$ (0.0001) | | 1.25 (0.5353) |
| Observations | 1884 | 1884 | 924 | 924 | 926 | 936 |
| Adjusted. $R^2$ | 0.1064 | | 0.5098 | | 0.0757 | |

Table A-II presents the equivalent to Table IV in lin-lin form. The dependent variable is population weighted $PM_{2.5}$ exposure in country *i* in year *t* in absolute levels. Income terms are in 000s. Figures in parentheses are *t* statistics for regression coefficients and significance levels for the test statistics. *t* statistics are calculated based on clustered standard errors. Signs of income terms are not line with results in Tables IV and A-I, and turning points are not relevant. Thus, these results indicate that EKC relationships are somewhat sensitive to functional form and decision of it should be carefully evaluated.
Significance levels: $^{*}$ p < 0.1, $^{**}$ p < 0.05, $^{***}$ p < 0.01.

Table A-III
Regression results
Higher SDI countries
(log-log)

| | Higher SDI countries $N = 77$ | | | | | |
|---|---|---|---|---|---|---|
| *T* | **1990 - 2017** $n = 924$ | | **1990-2010** $n = 385$ | | **2011 - 2017** $n = 539$ | |
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | 0.2674<br>(1.19) | 0.3252<br>(1.43) | 0.2380<br>(1.38) | 0.3085<br>(1.66) | -2.1571<br>(-1.43) | -1.6688<br>(-1.20) |
| $(\ln GDP/P)^2$ | -0.0140<br>(-1.18) | -0.0179<br>(-1.50) | -0.0106<br>(-1.10) | -0.0154<br>(-1.49) | 0.1062<br>(1.43) | 0.0745<br>(1.09) |
| Constant | 1.7041<br>(1.60) | 1.5013<br>(1.39) | $1.6629^{*}$<br>(2.15) | 1.4389<br>(1.73) | 13.869<br>(1.81) | 11.987<br>(1.71) |
| Turning point | 14,045 | 8,811 | 75,088 | 22,460 | 73,130(-) | 25,740(-) |
| *p*<br>AR(1) | $0.661^{***}$<br>(22.24) | $0.658^{***}$<br>(22.13) | $0.300^{***}$<br>(6.17) | $0.297^{***}$<br>(6.15) | $0.567^{***}$<br>(12.45) | $0.569^{***}$<br>(12.48) |
| Breusch-Pagan test | 0.66<br>(0.5160) | 0.68<br>(0.5072) | 0.17<br>(0.8406) | 0.18<br>(0.8355) | 1.43<br>(0.2413) | 1.41<br>(0.2455) |
| Wald test | $25,265^{***}$<br>(0.0000) | | $25,920^{***}$<br>(0.0000) | | $12,499^{***}$<br>(0.0000) | |
| Chow *F*-test | 0.22<br>(0.7994) | 0.85<br>(0.6528) | | | | |
| Hausman test | | $27.98^{***}$<br>(0.0000) | | $32.91^{***}$<br>(0.0000) | | - |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 924 | 924 | 385 | 385 | 539 | 539 |
| Adjusted. $R^2$ | 0.6306 | | 0.0672 | | 0.6246 | |

Table A-III is equivalent to Table V for the sub sample of Higher SDI countries. Columns 1 and 2 are the same as in column 3 and 4 in Table IV. There is no evidence of an EKC for Higher SDI countries in none of the sup periods, and the results in column 3 and 4 of Table IV is thus not sensitive to the of estimation period.

Table A-IV
Regression results
Lower SDI countries
(log-log)

| | Lower SDI countries $N$ = 78 | | | | | |
|---|---|---|---|---|---|---|
| *T* | **1990 - 2017** ***n* = 936** | | **1990-2010** ***n* = 390** | | **2011 - 2017** ***n* = 546** | |
| Model | Fixed effects | Random effects | Fixed effects | Random effects | Fixed effects | Random effects |
| ln GDP/P | $0.2782^{***}$ (2.47) | $0.2630^{**}$ (2.36) | 0.0508 (0.27) | 0.0258 (0.14) | $1.6980^{***}$ (2.95) | $1.3650^{***}$ (2.70) |
| $(\ln GDP/P)^2$ | $-0.0164^{**}$ (-2.49) | $-0.0156^{**}$ (-2.39) | -0.0017 (-0.14) | -0.0004 (-0.03) | $-0.1161^{***}$ (-3.40) | $-0.0915^{***}$ (-3.06) |
| Constant | $2.3104^{***}$ (4.83) | $2.3790^{***}$ (4.98) | $3.1822^{***}$ (4.35) | $2.2969^{***}$ (4.59) | -2.5905 (-1.05) | -1.5526 (-0.72) |
| Turning point | 4,826 | 4,580 | 3,082,269 | $1.014 \times 10^{14}$ | 1,499 | 1,735 |
| *p* AR(1) | $0.667^{***}$ (24.25) | $0.678^{***}$ (24.25) | $0.518^{***}$ (8.79) | $0.517^{***}$ (8.80) | $0.545^{***}$ (14.19) | $0.551^{***}$ (14.36) |
| Breusch-Pagan test | $4.13^{**}$ (0.0164) | $4.19^{**}$ (0.0155) | 1.43 (0.2413) | 1.55 (0.2140) | $43.10^{**}$ (0.0457) | $4.00^{**}$ (0.0189) |
| Wald test | $2,775^{***}$ (0.0000) | | $12,334^{***}$ (0.0000) | | $3,528^{***}$ (0.0000) | |
| Chow *F*-test | 0.28 (0.7539) | 0.54 (0.7633) | | | | |
| Hausman test | | 3.56 (0.1688) | | 4.40 (0.1105) | | - |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 936 | 936 | 390 | 390 | 546 | 546 |
| Adjusted. $R^2$ | 0.1334 | | 0.0786 | | 0.1385 | |

Table A-IV is the equivalent to Table V for the sub sample of Lower SDI countries. Columns 1 and 2 are the same as column 5 and 6 in Table IV. The results are in line with results found in Table IV, and indicates that the EKC relationship is significant for estimations based both on the full period and the sub period 2011-2017. There are not significant results for the sub period 1990-2010 which is line with the World results in Table V.

Figure A-I

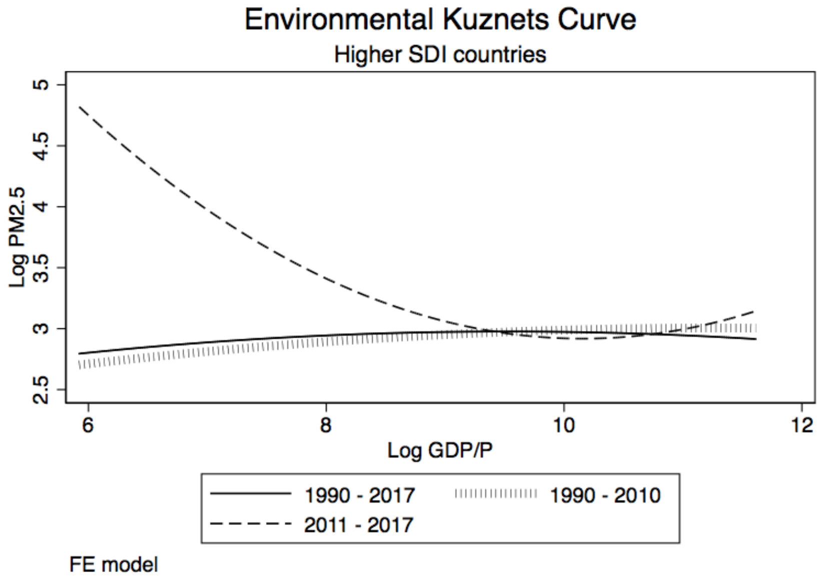



Figure A-I illustrates the estimated EKCs from the fixed effects model based on different time periods for the sub sample of Higher SDI countries. The figure is equivalent to figure VI for the sub sample of Higher SDI countries.

Figure A-II

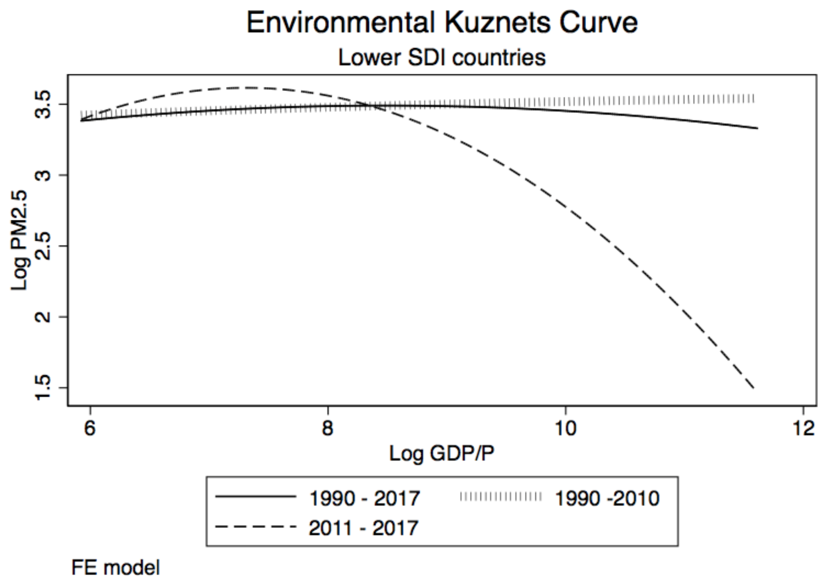



Figure A-II illustrates the estimated EKCs from the fixed effects model based on different time periods for the sub sample of Lower SDI countries. The figure is equivalent to figure VI for the sub sample of Lower SDI countries.

Table A-V

| | Estimated country fixed effects, $a_i$ | | | | |
|---|---|---|---|---|---|
| **Country** | **World 1990 - 2017** | **World 1990 - 2010** | **World 2011 - 2017** | **Higher SDI 1990 - 2017** | **Lower SDI 1990 - 2017** |
| Albania | -0,184 | -0,122 | -0,260 | 0,128 | |
| Algeria | 0,378 | 0,357 | 0,394 | | 0,150 |
| Angola | 0,308 | 0,362 | 0,151 | | 0,078 |
| Antigua and Barbuda | -0,141 | -0,149 | -0,060 | 0,142 | |
| Argentina | -0,444 | -0,432 | -0,374 | -0,157 | |
| Armenia | 0,359 | 0,405 | 0,237 | 0,679 | |
| Australia | -0,827 | -0,913 | -0,465 | -0,583 | |
| Austria | -0,455 | -0,516 | -0,107 | -0,213 | |
| Azerbaijan | -0,105 | -0,074 | -0,070 | 0,195 | |
| Bahrain | 1,087 | 0,925 | 1,481 | | |
| Bangladesh | 0,990 | 0,999 | 0,785 | | 0,747 |
| Barbados | 0,078 | 0,090 | 0,106 | 0,369 | |
| Belarus | -0,124 | -0,074 | -0,090 | 0,172 | |
| Belgium | -0,437 | -0,491 | -0,120 | -0,193 | |
| Belize | 0,051 | 0,102 | -0,081 | | -0,177 |
| Benin | 0,383 | 0,423 | 0,148 | | 0,134 |
| Bhutan | 0,496 | 0,523 | 0,381 | | 0,265 |
| Bolivia | 0,009 | 0,081 | -0,165 | | -0,221 |
| Botswana | 0,001 | -0,002 | 0,031 | | -0,228 |
| Brazil | -0,509 | -0,487 | -0,504 | | -0,737 |
| Brunei | -1,151 | -1,363 | -0,542 | -0,954 | |
| Bulgaria | -0,089 | -0,030 | -0,075 | 0,206 | |
| Burkina Faso | 0,534 | 0,574 | 0,289 | | 0,276 |
| Burundi | 0,562 | 0,525 | 0,432 | | 0,285 |
| Cameroon | 0,987 | 1,027 | 0,771 | | 0,749 |
| Canada | -1,085 | -1,158 | -0,742 | -0,841 | |
| Cape Verde | 0,297 | 0,305 | 0,160 | | 0,064 |
| Central African Republic | 0,859 | 0,798 | 0,759 | | 0,582 |
| Chad | 0,932 | 0,969 | 0,691 | | 0,680 |
| Chile | 0,001 | 0,003 | 0,122 | 0,285 | |
| China | 0,910 | 0,934 | 0,898 | | 0,678 |
| Colombia | -0,252 | -0,209 | -0,292 | 0,054 | |
| Comoros | -0,147 | -0,125 | -0,360 | | -0,389 |
| Congo | 0,579 | 0,573 | 0,438 | | 0,348 |
| Costa Rica | -0,304 | -0,284 | -0,296 | -0,004 | |
| Cote d'Ivoire | -0,033 | -0,017 | -0,233 | | -0,271 |
| Cyprus | -0,201 | -0,251 | 0,025 | 0,058 | |
| Czech Republic | -0,220 | -0,195 | -0,043 | 0,046 | |
| Democratic Republic of the Congo | 0,654 | 0,593 | 0,529 | | 0,377 |

| **Country** | **World 1990 - 2017** | **World 1990 - 2010** | **World 2011 - 2017** | **Higher SDI 1990 - 2017** | **Lower SDI 1990 - 2017** |
|---|---|---|---|---|---|
| Denmark | -0,681 | -0,761 | -0,320 | -0,442 | |
| Dominica | -0,118 | -0,069 | -0,210 | 0,192 | |
| Dominican Republic | -0,471 | -0,437 | -0,497 | -0,166 | |
| Ecuador | -0,338 | -0,278 | -0,425 | -0,028 | |
| Egypt | 1,134 | 1,088 | 1,116 | | 0,906 |
| El Salvador | 0,166 | 0,236 | 0,005 | | -0,063 |
| Equatorial Guinea | 0,727 | 0,675 | 0,971 | | 0,487 |
| Ethiopia | 0,454 | 0,410 | 0,253 | | 0,188 |
| Federated States of Micronesia | -0,648 | -0,555 | -0,899 | | -0,885 |
| Fiji | -0,688 | -0,636 | -0,814 | -0,371 | |
| Finland | -1,238 | -1,297 | -0,928 | -0,990 | |
| France | -0,508 | -0,550 | -0,230 | -0,258 | |
| Gabon | 0,546 | 0,485 | 0,616 | | 0,316 |
| Georgia | -0,011 | 0,045 | -0,126 | 0,307 | |
| Germany | -0,487 | -0,528 | -0,159 | -0,244 | |
| Ghana | 0,233 | 0,270 | 0,027 | | -0,005 |
| Greece | -0,257 | -0,275 | -0,124 | 0,013 | |
| Grenada | 0,046 | 0,092 | -0,005 | 0,351 | |
| Guatemala | 0,133 | 0,202 | -0,024 | | -0,096 |
| Guinea | -0,023 | -0,024 | -0,230 | | -0,275 |
| Guinea-Bissau | 0,187 | 0,190 | -0,015 | | -0,068 |
| Guyana | 0,009 | 0,061 | -0,139 | | -0,221 |
| Haiti | -0,352 | -0,312 | -0,582 | | -0,604 |
| Honduras | 0,028 | 0,120 | -0,204 | | -0,206 |
| India | 1,281 | 1,271 | 1,144 | | 1,046 |
| Indonesia | -0,354 | -0,313 | -0,431 | | -0,582 |
| Iran | 0,455 | 0,403 | 0,547 | 0,745 | |
| Iraq | 0,953 | 0,931 | 0,994 | | 0,725 |
| Ireland | -0,884 | -0,971 | -0,437 | -0,647 | |
| Israel | -0,019 | -0,075 | 0,228 | 0,243 | |
| Italy | -0,217 | -0,277 | 0,042 | 0,035 | |
| Jamaica | -0,507 | -0,449 | -0,642 | -0,192 | |
| Japan | -0,554 | -0,632 | -0,254 | -0,304 | |
| Jordan | 0,295 | 0,306 | 0,207 | 0,609 | |
| Kazakhstan | -0,482 | -0,452 | -0,364 | -0,198 | |
| Kenya | 0,155 | 0,152 | -0,039 | | -0,086 |
| Kiribati | -0,670 | -0,602 | -0,920 | | -0,918 |
| Kyrgyzstan | 0,023 | 0,085 | -0,212 | | -0,216 |
| Laos | 0,129 | 0,168 | -0,044 | | -0,106 |
| Lebanon | 0,211 | 0,182 | 0,240 | 0,510 | |

| Country | World 1990 - 2017 | World 1990 - 2010 | World 2011 - 2017 | Higher SDI 1990 - 2017 | Lower SDI 1990 - 2017 |
|---|---|---|---|---|---|
| Lesotho | 0,234 | 0,259 | 0,013 | | -0,011 |
| Luxembourg | -0,571 | -0,740 | 0,111 | -0,379 | |
| Macedonia | 0,333 | 0,398 | 0,273 | 0,638 | |
| Madagascar | -0,036 | -0,067 | -0,211 | | -0,292 |
| Malawi | 0,090 | 0,093 | -0,113 | | -0,178 |
| Malaysia | -0,308 | -0,343 | -0,137 | -0,028 | |
| Mali | 0,445 | 0,495 | 0,201 | | 0,194 |
| Malta | -0,419 | -0,447 | -0,179 | -0,155 | |
| Marshall Islands | -0,731 | -0,630 | -0,981 | | -0,967 |
| Mauritania | 0,588 | 0,627 | 0,379 | | 0,352 |
| Mauritius | -0,485 | -0,484 | -0,405 | -0,192 | |
| Mexico | -0,002 | 0,000 | 0,037 | 0,289 | |
| Mongolia | 0,488 | 0,463 | 0,475 | 0,801 | |
| Morocco | 0,197 | 0,208 | 0,082 | | -0,033 |
| Mozambique | 0,002 | -0,013 | -0,214 | | -0,274 |
| Myanmar | 0,509 | 0,545 | 0,307 | | 0,266 |
| Namibia | 0,080 | 0,109 | -0,003 | | -0,148 |
| Nepal | 1,374 | 1,348 | 1,183 | | 1,125 |
| Netherlands | -0,486 | -0,543 | -0,129 | -0,247 | |
| New Zealand | -1,241 | -1,298 | -0,970 | -0,984 | |
| Nicaragua | -0,170 | -0,079 | -0,390 | | -0,403 |
| Niger | 1,234 | 1,237 | 1,050 | | 0,961 |
| Nigeria | 0,902 | 0,960 | 0,720 | | 0,670 |
| Norway | -1,012 | -1,135 | -0,507 | -0,794 | |
| Oman | 0,563 | 0,400 | 0,940 | 0,805 | |
| Pakistan | 0,908 | 0,937 | 0,729 | | 0,675 |
| Panama | -0,634 | -0,621 | -0,537 | -0,343 | |
| Papua New Guinea | -0,555 | -0,484 | -0,787 | | -0,792 |
| Paraguay | -0,601 | -0,557 | -0,671 | | -0,828 |
| Peru | 0,157 | 0,203 | 0,103 | 0,467 | |
| Philippines | -0,161 | -0,087 | -0,330 | | -0,391 |
| Poland | 0,020 | 0,068 | 0,142 | 0,300 | |
| Portugal | -0,931 | -0,956 | -0,764 | -0,663 | |
| Puerto Rico | -0,924 | -1,043 | -0,608 | -0,669 | |
| Romania | -0,384 | -0,337 | -0,317 | -0,096 | |
| Russian Federation | -0,278 | -0,273 | -0,134 | | -0,510 |
| Rwanda | 0,610 | 0,603 | 0,390 | | 0,350 |
| Saint Lucia | 0,030 | 0,073 | -0,024 | 0,333 | |
| Saint Vincent and the Grenadines | 0,012 | 0,068 | -0,076 | 0,322 | |
| Samoa | -0,631 | -0,565 | -0,814 | | -0,861 |

| Country | World 1990 - 2017 | World 1990 - 2010 | World 2011 - 2017 | Higher SDI 1990 - 2017 | Lower SDI 1990 - 2017 |
|---|---|---|---|---|---|
| Saudi Arabia | 1,280 | 1,050 | 1,777 | | |
| Senegal | 0,445 | 0,472 | 0,232 | | 0,205 |
| Seychelles | -0,129 | -0,165 | 0,039 | 0,149 | |
| Sierra Leone | -0,162 | -0,175 | -0,363 | | -0,421 |
| Singapore | -0,111 | -0,304 | 0,559 | 0,099 | |
| Solomon Islands | -0,614 | -0,558 | -0,858 | | -0,860 |
| South Africa | 0,061 | 0,044 | 0,055 | 0,365 | |
| South Korea | 0,182 | 0,142 | 0,452 | 0,447 | |
| Spain | -0,758 | -0,798 | -0,528 | -0,499 | |
| Sri Lanka | 0,025 | 0,211 | -0,142 | 0,338 | |
| Sudan | 0,726 | 0,720 | 0,559 | | 0,489 |
| Suriname | 0,137 | 0,163 | 0,140 | 0,436 | |
| Swaziland | -0,328 | -0,301 | -0,442 | | -0,556 |
| Sweden | -1,194 | -1,260 | -0,838 | -0,952 | |
| Switzerland | -0,617 | -0,708 | -0,175 | -0,393 | |
| Tajikistan | 0,700 | 0,742 | 0,465 | | 0,455 |
| Tanzania | 0,181 | 0,202 | -0,041 | | -0,066 |
| Thailand | 0,194 | 0,219 | 0,206 | 0,493 | |
| The Bahamas | -0,170 | -0,223 | 0,022 | 0,091 | |
| The Gambia | 0,302 | 0,317 | 0,091 | | 0,049 |
| Togo | 0,358 | 0,384 | 0,136 | | 0,100 |
| Tonga | -0,702 | -0,624 | -0,905 | | -0,933 |
| Trinidad and Tobago | 0,140 | 0,124 | 0,365 | 0,409 | |
| Tunisia | 0,360 | 0,353 | 0,324 | | 0,132 |
| Turkey | 0,569 | 0,512 | 0,737 | 0,853 | |
| Turkmenistan | -0,038 | -0,005 | -0,037 | 0,267 | |
| Uganda | 0,706 | 0,672 | 0,513 | | 0,449 |
| Ukraine | -0,086 | 0,008 | -0,246 | 0,230 | |
| United Arab Emirates | 0,616 | 0,367 | 1,154 | 0,819 | |
| United Kingdom | -0,656 | -0,706 | -0,364 | -0,405 | |
| United States | -0,938 | -1,024 | -0,524 | -0,707 | |
| Uruguay | -0,852 | -0,838 | -0,771 | -0,563 | |
| Uzbekistan | 0,237 | 0,314 | 0,039 | 0,565 | |
| Vanuatu | -0,629 | -0,552 | -0,876 | | -0,868 |
| Vietnam | 0,352 | 0,421 | 0,156 | | 0,117 |
| Yemen | 0,697 | 0,674 | 0,530 | | 0,461 |
| Zambia | 0,168 | 0,232 | -0,060 | | -0,070 |
| Zimbabwe | -0,070 | -0,052 | -0,283 | | -0,314 |

Table A-V presents the estimated country fixed effects from the different sub sample and –time EKC estimations. Columns 1-3 list the country fixed effects from models in col 1, 3 and 5 in Table V, while columns 4 and 5 lists the country specific effects from models in column 3 and 5 in Table IV.

# Appendix B

Table B-I

| **Preference** | **Definition** | **Weight** |
|---|---|---|
| Patience | Intertemporal choice sequence using staircase method | 0.71 |
| | Self-assessment: Willingness to wait | 0.29 |
| Risk taking | Lottery choice sequence using staircase method | 0.47 |
| | Self-assessment: Willingness to take risks in general | 0.53 |
| Positive reciprocity | Self-assessment: Willingness to return a favour | 0.48 |
| | Gift in exchange for help | 0.52 |
| Negative reciprocity | Self-assessment: Willingness to take revenge | 0.37 |
| | Self-assessment: Willingness to punish unfair behaviour towards self | 0.265 |
| | Self-assessment: Willingness to punish unfair behaviour towards others | 0.265 |
| Altruism | Donation decision | 0.54 |
| | Self-assessment: Willingness to give to good causes | 0.46 |
| Trust | Self-assessment: People have only the best intentions | 1 |

Table B-I reports the weights and wording of preferences as in Falk et.al. (2018). For further details and wording of survey items see appendix in Falk et al. (2018).

Figure B-I

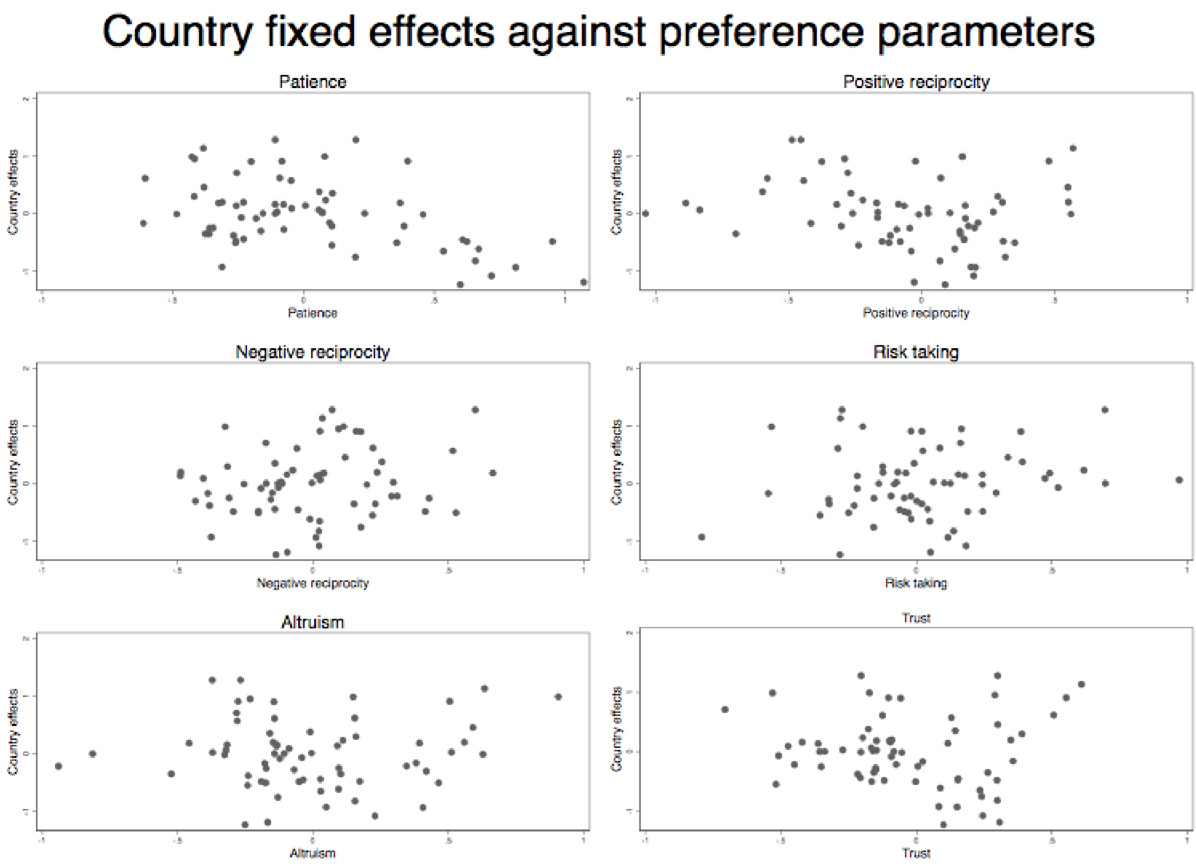



Figure B-I shows correlation plots of estimated country fixed effects of pollution and preference parameters. Country fixed effects are the individual fixed effects retrieved from the FE-estimation of the World sample using all observations 1990-2017 (col 1, table IV). Country effects on vertical axis and preference parameter on horizontal axis.

TABLE B-II
Regression results
Tanzania and negative reciprocity
(log-log)

| *Sample* | (original sub sample) **Negative reciprocity > 0** **N = 33** | (original sub sample) **Negative reciprocity < 0** **N = 33** | (modified to include Tanzania) **Negative reciprocity < 0** **N = 34** |
|---|---|---|---|
| Model | Fixed effects | Fixed effects | Fixed effects |
| ln GDP/P | 0.7652$^{***}$ | 0.7375$^{***}$ | 0.7617$^{***}$ |
| | (4.17) | (5.05) | (5.26) |
| (ln GDP/P)$^2$ | 0.7652$^{***}$ | -0.0437$^{***}$ | -0.0451$^{***}$ |
| | (4.17) | (-4.18) | (-4.34) |
| Constant | -0.2037 | 0.0782 | -0.0222 |
| | (-0.24) | (0.15) | (-0.04) |
| Turning point | 12,094 | 4,620 | 4,650 |
| *p* | 0.684$^{***}$ | 0.684$^{***}$ | 0.782$^{***}$ |
| AR(1) | (16.73) | (16.71) | (17.28) |
| Breusch-Pagan | 2.33$^{*}$ | 1.89 | 1.91 |
| test | (0.0990) | (0.1528) | (0.1487) |
| Wald test | 48,177$^{***}$ | 21,844$^{***}$ | 3,980$^{***}$ |
| | (0.0000) | (0.0000) | (0.0000) |
| Chow *F*-test | | | 4.32$^{**}$ |
| | | | (0.0216) |
| Time effects | Yes | Yes | Yes |
| Observations | 936 | 936 | 408 |
| Adjusted. $R^2$ | 0. 3472 | 0. 4014 | 0. 3984 |

Table B-II presents the FE estimation behind figure XI in subsection 6.2.3.2 Figure XI illustrates the models in column 1 and 3. The Chow-test rejects equal slope coefficients for the original and the modified sub samples of countries with lower levels of negative reciprocity in columns 2 and 3. This is thus the reason why the estimation results for the modified group is chosen to be the base of the back-of-the calculation and illustration in section 6.2.3.2. The modified sub sample includes Tanzania which is hypothesized to score below zero on negative reciprocity in the example. Significance levels: $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

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