Carbon Curse in Developed Countries*

Mireille Chiroleu-Assouline†, Mouez Fodha‡ and Yassine Kirat§

31 January 2018

Preliminary Draft

Abstract

This paper investigates empirically the relationship between natural resource endowment and CO_2 emission. We use panel data on 29 countries (OECD and BRICS) over the 1995-2009 period. We first estimate the relationship between national CO_2 emissions per GDP and resource abundance, at a macroeconomic level. Our results show that there exists a carbon curse: countries rich in coal, oil and gas emit more CO_2 to generate the same amount of economic output as countries where fossil fuels are scarce. We then use these econometric results to assess the consequences of abundance on the sectorial emissions for two groups of countries, depending on their resource endowments. We estimate the relationship between sectorial CO_2 emissions per value added, abundance, technology level, environmental policy stringency, corruption, the energy mix, cooling and heating degree days. We find that a country rich in fossil fuels pollutes more in resource-related sectors, but also in all other sectors of the economy, even in the service sectors. We conclude that there is a spreading process of the polluting practices in resource rich countries.

Keywords: carbon curse, carbon intensity, resource-rich economies.

JEL codes: Q32 - Q53.

1 Introduction

Defining the best response to fight climate change is nowadays one of the most important policy issues. The effectiveness of the *Paris Agreement* is uncertain, protectionist policies are increasingly being implemented

*This research has been funded by the French Ministery for Environment and the program Investissements d'Avenir of the French government (ANR-10-LABX-93-01).

†Paris School of Economics, University of Paris 1 Panthéon-Sorbonne, France. Email : Mireille.Chiroleu-Assouline@univ-paris1.fr.

‡Paris School of Economics, University of Paris 1 Panthéon-Sorbonne, France. Email : Mouez.Fodha@univ-paris1.fr.

§Paris School of Economics, University of Paris 1 Panthéon-Sorbonne, France. Email : Yassine.Kirat@univ-paris1.fr.

and environmental policies are being overshadowed in times of economic crisis. These potential failures to mitigate CO_2 emissions could also be explained by an imperfect diagnosis about the causes of the increase in CO_2 emissions. CO_2 emissions are usually explained by industrial production, transport and heating, in addition to the energy mix. The more fossil fuels are important in the energy mix, and the higher the CO_2 emissions will be. Regulating these sources may harm incomes and national revenues, firm competitiveness, mobility and agents' purchasing power. These detrimental economic consequences may explain the public opposition to any environmental regulation and the reluctance of certain countries to take strong commitments. We argue that, in addition to these usual explanations of CO_2 emissions, natural resource abundance plays a crucial role. Our work starts from the following observation. Fossil natural resources and the associated sectors, like (i) extraction, (ii) energy production (refining...), together with the use of fossil fuels, are polluting. Thus, a fossil resource-rich country can also easily be a country with significant CO_2 emissions. The relationships between resources and economic growth had already been widely discussed by the literature. Studies conclude that there exists links between natural resources and economic growth (resource curse) and also interactions between pollution levels and economic growth (the Environmental Kuznets Curve "EKC"). Our work is at the crossroads of these two fields (resource curse and EKC), since we investigate the relationship between natural resources and CO_2 pollution, in order to test the validity of the carbon curse theory (Friedrichs and Inderwildi (2013)). According to the latter article, countries rich in coal, oil and gas emit more CO_2 to generate the same amount of economic output as countries where fossil fuels are scarce.

Our research questions are as follows. To what extent is a country rich in fossil fuels more polluting than another country? If a country rich in fossil fuels pollutes more in resource-related sectors, are similarly high levels of pollution observed also in other sectors of the economy? i.e. Is there any effect of spreading polluting practices to all sectors of the economy? What could be the underlying mechanisms of the carbon curse and of the spreading process?

The objective of this paper is to contribute to the debate on climate change mitigation by measuring the consequences of the abundance in fossil energy on the emissions at different levels: national and sectorial. Our empirical analysis relies on panel data including 29 countries, over the 1995-2009 period, which reveals considerable heterogeneity between countries. We also use sectorial data that take into account 7 sectors.

This paper is related to two strands of the literature: the first strand investigates the link between economic growth and pollution emissions (EKC), and the second one analyses the interactions between natural resources and economic growth (resource curse).

The first strand, the environmental consequences of economic growth, has been the subject of intense research over the past few decades. A number of pieces of empirical work have suggested that there is an inverted U-shaped relationship between economic growth, usually measured in terms of income per capita, and pollution emission (this environmental pattern has been called the Environmental Kuznets Curve, EKC). At the first stage of economic growth environmental degradation increases as per capita income increases, but begins to decrease as rising per capita income passes beyond a turning point. According to EKC hypothesis, economic growth could be the remedy to environmental problems in the long-term. Since the beginning of the 1990's, the EKC has become an independent and essentially empirical research domain, following the work of Grossman and Krueger (1995), Shafik and Bandyopadhyay (1992), Panayotou (1993), Selden and Song (1994) and Galeotti (2007). However, the conclusions from this empirical work are ambiguous. On the one hand, some research has confirmed the existence of an EKC for different measurements of environmental degradation, e.g. Panayotou (1993) and Selden and Song (1994). On the other hand, a number of authors affirm that there is no evidence of the EKC and rather find a monotonically increasing or decreasing relationship between pollution and per capita income, e.g. Holtz-Eakin and Selden (1995), Torras and Boyce (1998), Hettige et al. (2000), de Bruyn et al. (1998) and Roca et al. (2001). The sources of discrepancies between the empirical results stem mainly from the nature and level of aggregation of the data (time series, cross-section or panel) and the pollutant under consideration. Nevertheless, the work on CO_2 tends to show an ever-increasing relationship between GDP and emissions.

The second strand of the literature analyzes the interactions between growth and natural resources. Following the seminal work of Sachs and Warner (1995), a huge literature has developed on the so-called resource curse. The latter refers to the paradox that resource-abundant countries experience lower long run economic growth than do resource-poor countries. Five major transmission channels have been identified in the literature to explain the resource curse. The most popular is the "Dutch disease", which has been widely documented in the literature (see for example Corden, 1984; Krugman (1987); Bruno and Sachs (1982); Torvik (2001); Matsen and Torvik (2005)). This refers to the deterioration in the terms of trade that results from the real exchange-rate appreciation following a resource boom. This shift in the terms of trade has a negative impact on non-resource sectors. A second channel is the potential negative effect of natural resources on education. Following Gylfason (2001) and Sachs and Warner (1999), the abundance of natural resources increases the agents' opportunity cost of human-capital investment. The third channel refers to institutional quality. Resources may induce rent-seeking behaviors, which reduce institutional quality (a major determinant of economic growth) through corruption or armed conflict (see Jensen and Wantchekon (2004); Robinson et al. (2006); Adani et al. (2014)). Natural resources may also crowd out physical-capital investment (Sachs and Warner (1995)). A resource boom implies a shift in the distribution of production factors, from the secondary and tertiary sectors to the primary sector. As the manufacturing and tertiary sectors are more likely to exhibit increasing returns to scale and positive externalities than the primary sector, this shift will reduce productivity and the profitability of investment. Last, the volatility in resource prices could increase macroeconomic instability, which in turn inhibits growth (Van der Ploeg & Poelhekke, 2009). Alongside this literature on the transmission channels of the resource curse, there are great debates over the evidences for the resource curse.

We are interested in the intersection between these two branches. We deeply analyze the interactions between natural resources and pollution. We investigate empirically the carbon curse assumption (Friedrichs and Inderwildi (2013)), to verify whether a higher abundance of fossil fuels implies higher carbon intensity. The main intuitions for the carbon curse are as follows: first, a scale effect induced by the predominance of fossil fuel sectors which emit massively CO_2; second, crowding out effects in the energy generation sector, forming a barrier to the development of renewable energy sources; third, spreading effects in other sectors of the economy combined with less stringent policies. Very few fuel-rich countries avoid the carbon curse – except for those suffering from the resource curse. However the literature on EKC and resource curse often points out the crucial role of economic development and of the quality of institutions. By focusing on a group of developed countries, we highlight the importance of a novel argument based on resource abundance.

Our article is close to Friedrichs and Inderwildi (2013), but we differ from them by our empirical approach that takes into account both macro and sectorial data for a group of developed countries. While their paper and intuitions are based on descriptive statistics, we apply econometric methods to provide detailed evidence for the carbon curse assumption, and to explain its mechanisms.

The question addressed in the current paper is how resource endowment influence carbon emission, at a national and a sectorial basis; this focus distinguishes our paper from the related works. The first objective is to evaluate the relationship between abundance and CO_2 emission at a country level. We then use these econometric results to assess the consequences of abundance on the sectorial emissions for two groups of countries.

Our results show that there is a U-shaped relationship at a country level between CO_2 intensity of GDP and resource endowment at a country level: above a turning point, the more a country is fossil resource rich, the more this country will emit CO_2. We also show that there exists a spreading effect among all sectors of the country, even services sectors. We also find that national CO_2 intensity are explained by the energy mix, the environmental policy stringency and the technological level. In order to explain this U-shaped relationship at a country level, we rely on a sectorial analysis using sectorial CO_2 emissions intensity. The results show that abundance has a different the sectorial CO_2 intensity across sectors. Interestingly, fuel rich and relatively poor fuel countries show opposite results.

The remainder of the paper is structured as follows. Section 2 describes the data used. Section 3 presents the methodological approach and Section 4 the empirical findings. The interpretation of the results are presented in Section 5, and Section 6 concludes.

2 Data

To test for the carbon curse hypothesis, we undertake an econometric analysis for 29 countries over the full spectrum from resources rich to resources poor countries among OECD and BRIC (except Indonesia and Sweden, for data availability reasons).

This analysis is done using twofold estimation strategy with two nested datasets. In order to first estimate the size of the overall effect of resource endowment on CO_2 emissions, we use aggregated country data. This country wide analysis allows to assess the validity of the carbon curse concept by looking to the effect of energy resources abundance on the carbon intensity. Once this first assessment has been realized, we rely on country industry data to disentangle the overall country effect. The disaggregated sectorial data allows to test whether resource endowment alters the sector elasticity between resource rich and resource poor countries. In other words, we investigate if CO_2 efficiency of sectors differs between resource rich and resource poor countries, all other things being equal.

In order to complete our study, we need a variable related to the resource stock. Until now, the literature rely on proxies for natural resource abundance because of the lack of appropriate data. The most-used proxy for abundance in the literature is the Sachs and Warner variable, which corresponds to the ratio of natural resource exports to GDP. We argue that this proxy is an appropriate measure of the resource dependence, but not really of abundance, and that it is potentially endogenous when used in the resource curse literature. Thanks to the data series collected by the World Bank (1997, 2006, 2011), we avoid this endogeneity issue as Brunnschweiler and Bulte (2008), Ding and Field (2005) and Alexeev and Conrad (2009) have done already. However, does this variable offer a real improvement? The accuracy and reliability of the natural capital and specifically of the subsoil asset data were important concern for the authors of the World Bank study. Nevertheless, one might argue that the data availability is conditional to a country's technological level. However, the data on natural resource wealth are probably independent of local issues, and then enough exogenous for our goal. Especially, fuel and non-fuel mineral deposits which we focus on have been quite well explored and estimated due to the broad economic benefits they may confer. Also, the commitment of large multinational firms using similar technical approach to collect their information regardless of the local political and technological conditions confirm the exogeneity of our resource stock variable.

Finally, the measure of natural capital from World bank is innovative and gives novel insight into the magnitude of the natural capital. It can be used as a measure for the value of subsoil assets (the subsoil wealth measure values the principal fuel and non-fuel mineral stock present in a country) in US$ for cross-country or panel dataset.

The economy wide and sectorial dataset are described in subsections 2.1 and 2.2 respectively.

2.1 The country level dataset

The country level dataset covers yearly observations for 29 countries over the full spectrum from fuel rich to fuel poor countries among OECD and BRIC organizations over 1995-2009 period. In order to conduct an objective analysis, we keep the same countries in our two datasets. Overall, our sample accounts for 30% of the world CO_2 emissions. To assess the impact of resource endowment on CO_2 emissions, we collect several variables that together cover socioeconomics and climatic factors that the literature on anthropogenic country GHG emissions find to be relevant. Table(6) contains a general overview and papers supporting the variable use. Seven variables for each country are taken into account: Anthropogenic CO_2 emissions per US$ of GDP, Resource endowment, Environmental policy stringency, Alternative energy use, Technological level index and Corruption index.

Details and sources for these variables are given in Table A.1 in Appendix. Anthropogenic CO_2 emissions in kilo tons, Resource abundance, GDP per capita (PPP adjusted) and technological level which is approximated by the count of filed patents, are taken from the World Bank. A patent is taken as an observation the year the patent is filed in a national patent authority from World Intellectual Property Organization (WIPO). Alternative energy use is measured as the share of clean and nuclear energy, in which clean energy is noncarbohydrate energy that does not produce carbon dioxide when generated. It includes hydropower and nuclear, geothermal, and solar power, among others. The OECD Environmental Policy Stringency Index (EPS) is a country-specific and internationally-comparable measure of the stringency of environmental policy. The index covers 28 OECD and 6 BRICS countries for the period 1990-2012. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behaviour. The index is based on the degree of stringency of 14 environmental policy instruments, primarily related to climate and air pollution. The indicator ranges from 0 (not stringent) to 6 (highest degree of stringency). cooling degree days (CDD) and heating degree days (HDD) are taken from Euro-Mediterranean Center for Climate Change, both allow us to capture climatic conditions. Heating and cooling degree days

(HDD and CDD) index the heating and cooling needs to neutralize the deviation of surface temperature from a standard comfort level. HDD and CDD are conventionally measured as the annual sums of negative and positive deviations of daily mean surface temperatures from a reference standard of 18.3° Celsius. Finally, the estimate of governance performance reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. It is taken from Worldwide Governance Indicators (WGI) and ranges from approximately -2.5 (weak) to 2.5 (strong).

2.2 Sector level dataset

The sector level dataset covers 35 sectors for 28 countries over 1995-2009 period and accounts for 30% of the world CO_2 emissions. The countries are the same as we have in the country database, except for Hungary because of the lack of data at the sector level. We also keep the same variables as in the country level database but use sectorial data when it is available and relevant. By aggregating the sectorial database according ISIC rev2 classification, we obtain 7 sectors, which allow to easily interpret and compare our results. The variables are the following.

Sectorial anthropogenic CO_2 and sectorial Value added are taken from the World Input Output Database. Given that the GHG policy stringency index measures national GHG policy stringency and natural resource is available at the country level also, all sectors may, to a greater or lesser extent, be affected.

For the sector-level estimation, we use a sectoral technology variable which corresponds to the share, in percentage, of sector-specific high-skilled working hours as compared to total sector-specific working hours. A relative increase in working hours of high-skilled is considered to be equivalent to an improvement in the sector-specific technology. Finally, the climatic and socio-demographic variables that are influencing the CO_2 emission are the same independently of the level of analysis (country or sectorial).

2.3 Descriptive statistics

Despite the fact that all the countries in our sample are at an advanced stage of development, there is considerable economic and environmental heterogeneity. Table 1 provides descriptive statistics by variable of interest, while Table 2 presents the averages by country over the period[1].

[1] Table 1 shows the average of all variables over the 1995-2009 period and for all countries. Table 2 shows the averages, this time by country. The min and max of table 1 are not the minimum and maximum of the averages, but the absolute minimum and maximum observed over all the data. For example, 1.1 is the CO_2 intensity for China in 1995.

Table 1: Summary statistics

Variable	Mean	SD	Min.	Max.
CO_2 Intensity (kg/US$)	0.34	0.16	0.11	1.1
Abundance (2005 US$)	$1.52.10^{11}$	$4.29.10^{11}$	1	$3.47.10^{12}$
Environmental policy stringency (0;6)	1.53	0.85	0.33	4.07
Heating degree days (°.nb days)	12354.43	5689.74	0.02	23174.28
Cooling degree days (°.nb days)	2156.92	2573.21	19.36	11921
Technological level (nb filed patents)	22219	65563	3	384201
Alternative (% total energy use)	11.85	11.77	0	50.73
Corruption (-2,5;2,5)	0.86	0.98	-1.13	2.58

Table 2: Variable means by country 1/2

Country	CO_2 Intensity	Abundance	Alternative energy	Env. Stringency
	(kg/$US)	(2005 US$)	(% of energy use)	Index (0;6)
Australia	0.47	$2.50.10^{11}$	1.36	1.29
Austria	0.20	$3.04.10^{9}$	11	2.34
Belgium	0.28	$4.43.10^{6}$	21	1.47
Brazil	0.15	$2.31.10^{11}$	14.52	0.45
Canada	0.44	$2.57.10^{11}$	20.59	1.52
China	0.79	$6.68.10^{11}$	2.65	0.67
Czech Republic	0.51	$1.98.10^{9}$	12.16	1.53
Denmark	0.24	$2.84.10^{10}$	2.12	2.61
Finland	0.32	$4.14.10^{8}$	20.45	2.14
France	0.17	$4.30.10^{9}$	44.81	1.95
Germany	0.27	$2.76.10^{11}$	13.47	2.39
Greece	0.31	$2.30.10^{9}$	1.95	1.75
Hungary	0.29	$8.72.10^{9}$	14.33	1.62
India	0.37	$2.49.10^{11}$	2.53	0.59
Indonesia	0.21	$2.14.10^{11}$	5.95	0.45
Ireland	0.25	$1.98.10^{9}$	0.98	1.26
Italy	0.21	$2.51.10^{10}$	4.63	1.82
Japan	0.27	$3.77.10^{9}$	17.41	1.57
South Korea	0.42	$4.98.10^{8}$	15.70	1.78
Netherlands	0.27	$2.71.10^{10}$	1.52	2.08
Poland	0.54	$2.77.10^{10}$	0.21	1.46
Portugal	0.22	$2.65.10^{8}$	4.80	1.75
Russia	0.68	$2.77.10^{12}$	7.88	0.54
Slovakia	0.41	$4.81.10^{8}$	23.98	1.16
Spain	0.83	$1.70.10^{9}$	15.42	2.27
Sweden	0.15	$1.84.10^{9}$	47.12	2.15
Turkey	0.23	$2.21.10^{10}$	5.49	0.86
United-Kingdom	0.26	$1.49.10^{11}$	10.22	1.46
United-States	0.42	$6.35.10^{11}$	10.81	1.52

Table 3: Variable means by country 2/2

Country	Heating DD	Cooling DD	Technological level	Corruption
	(°.nb days)	(°.nb days)	(nb filed patents)	(-2,5;2,5)
Australia	4337	3095	2262	1.92
Austria	18494	531	2073	2
Belgium	11643	1112	604	1.36
Brazil	759	7000	3476	−0.03
Canada	20883	876	4221	2
China	10297	3527	71598	−0.43
Czech Republic	16848	767	625	0.37
Denmark	12116	519	1599	2.44
Finland	21426	407	2116	2.44
France	12069	1177	13759	1.34
Germany	15262	810	47222	1.91
Greece	9117	3385	408	0.47
Hungary	14092	1348	778	0.57
India	1750	11296	3646	−0.39
Indonesia	0.1	10710	204	−0.85
Ireland	10969	61	882	1.58
Italy	10984	1647	7968	0.44
Japan	8483	2600	351313	1.13
South Korea	10180	2126	90068	0.38
Netherlands	11729	416	2299	2.17
Poland	15959	999	2375	0.39
Portugal	5182	1317	168	1.19
Russia	21439	1085	22612	−0.91
Slovakia	16060	1082	214	0.24
Spain	10089	2652	2773	1.22
Sweden	17021	392	3321	2.27
Turkey	12926	2830	788	−0.25
United-Kingdom	11559	350	18967	2
United-States	11291	3109	177772	1.6

The average national CO_2 intensities of the GDP range from 0.15 to 0.83, while the share of alternative energies varies from 0.21% to 47.12%. Similarly, the corruption index ranges from -0.91 to 2.44 (where negative values denote high levels of corruption), and goes hand in hand with the distribution of environmental stringency. The technological level index is also an important differentiation factor, with the largest (Japan) being more than 1500 times higher than the lowest (Indonesia).

These descriptive statistics do not allow for simple correlations between variables. Indeed, in a counter-intuitive way, Sweden and Brazil, for example, have the same CO_2 intensity while the second country is much richer in resources than the first. We also note that environmental stringency is probably not the main determinant of the CO_2 intensity of GDP: despite a much higher environmental severity and an apparently more favorable energy mix, Germany emits more CO_2 per unit of GDP than Turkey.

Figure 1 shows a ranking of the countries in our sample by increasing CO_2 intensity per unit of GDP. The highlighted countries are rich in resources. Of the eleven countries with the highest CO_2 intensity, seven are resource-rich countries. [2]

Atypical situations appear, such as resources-poor countries with high CO_2 emissions (Korea, Czech Republic, Poland, Bulgaria) and, at the other end of the spectrum, Brazil, a low emitter although richly endowed with mineral and fossil resources.

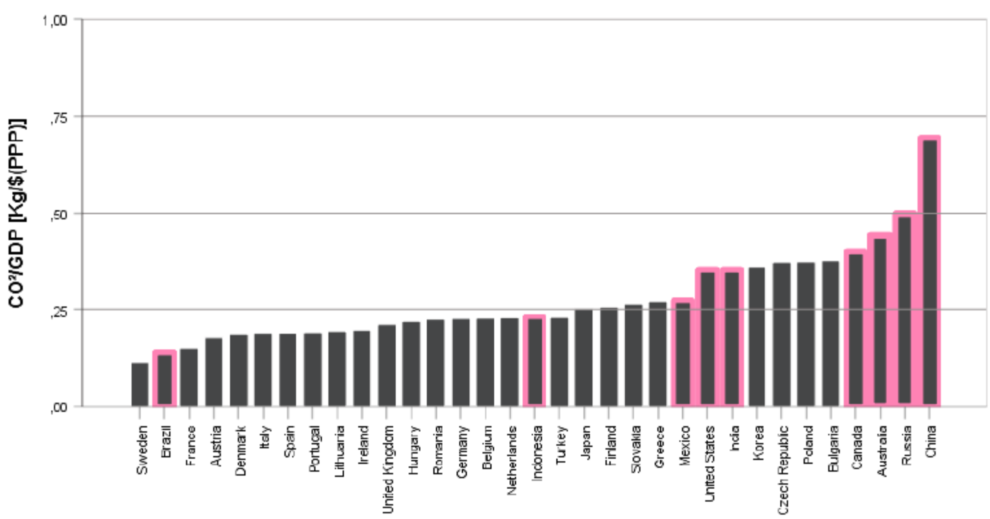

Figure 1: National carbon intensities in 2009. Resources-rich countries in pink.

[2] By restraining our panel to developed countries, we do not take into account the OPEC countries which are both very rich in fossil resources and highly CO_2 emitting (Friedrichs and Inderwildi (2013)).

Like in Friedrichs and Inderwildi (2013), Figure 2 plots decarbonization achieved in the different countries, defined as the reduction of CO_2 intensity over time, against average economic growth rates. Only one country (Indonesia) exhibits an emission intensification during the period, i.e. a negative decarbonization. The other countries form two groups: above the 45° line, decarbonization is linked to emission reduction while below this line, decarbonization occurs together with emission increase.

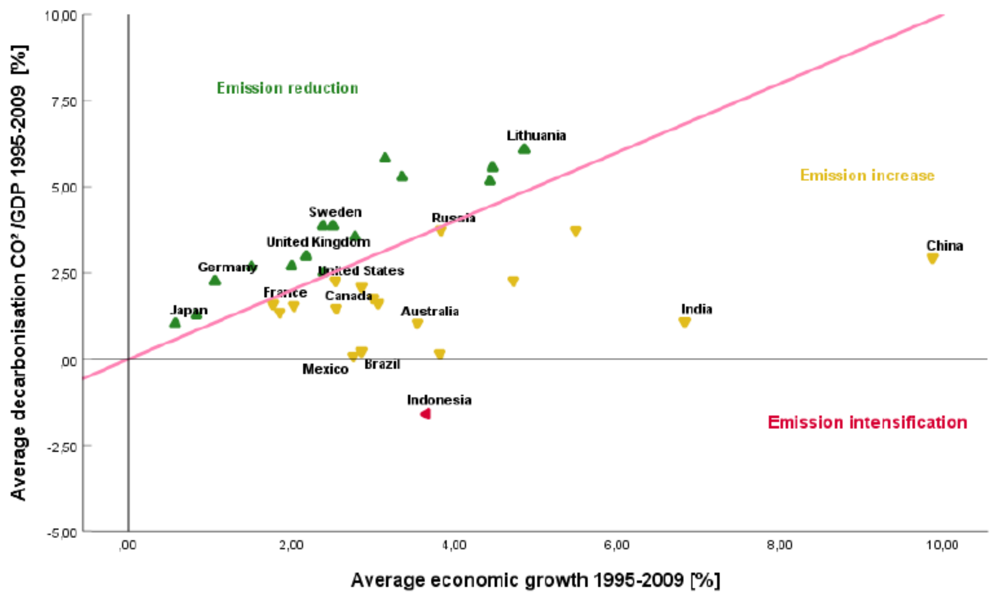

Figure 2: Carbon trajectories represented by the average annual increase or decrease of carbon intensity against average economic growth rates between 1995 and 2009.

A sectoral presentation of the data is provided in Figures 3A to 3C. The three main sectors presented are: mining and utilities, services, transport, storage and communication. In each figure, the CO_2 intensity of the sector is represented by its share of the country's GDP. Large solid black circles are associated with resource-rich countries, while small white circles represent resource-poor countries.

Figure 3B is perhaps the most striking: for a given share of the services sector's contribution to the country's GDP, the CO_2 intensity of the sector is highest for resource-rich countries.

➢ **Mining and utilities:**

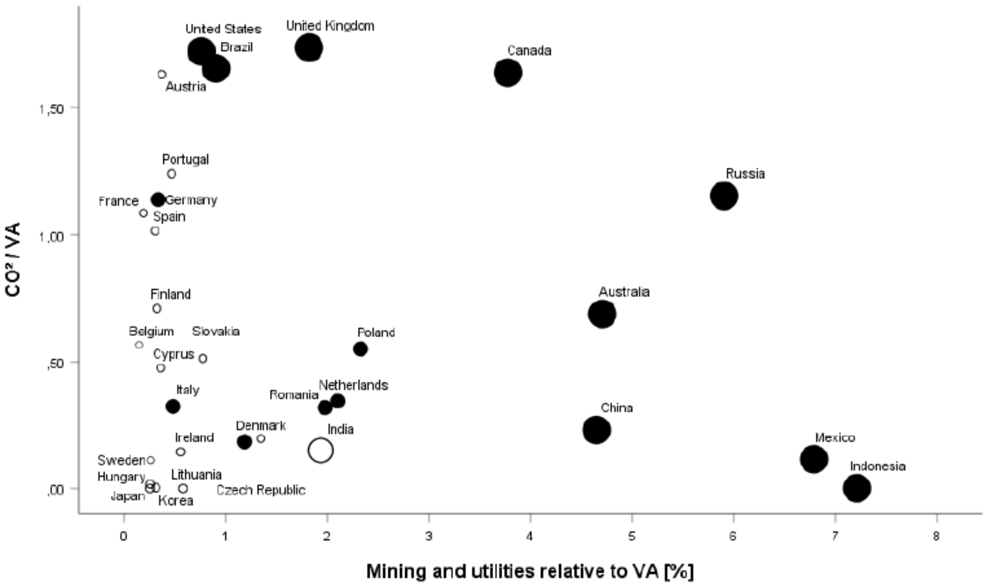

Figure 3A: Relationship between sectorial carbon intensity and the share of sector Value added in GDP.

➢ **Services**

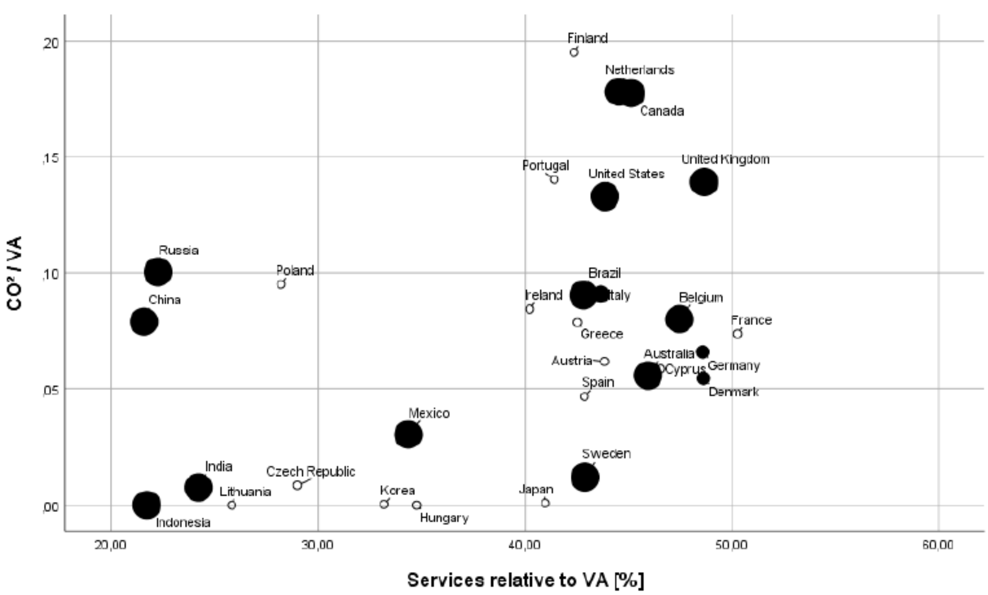

Figure 3B: Relationship between sectorial carbon intensity and the share of sector Value added in GDP.

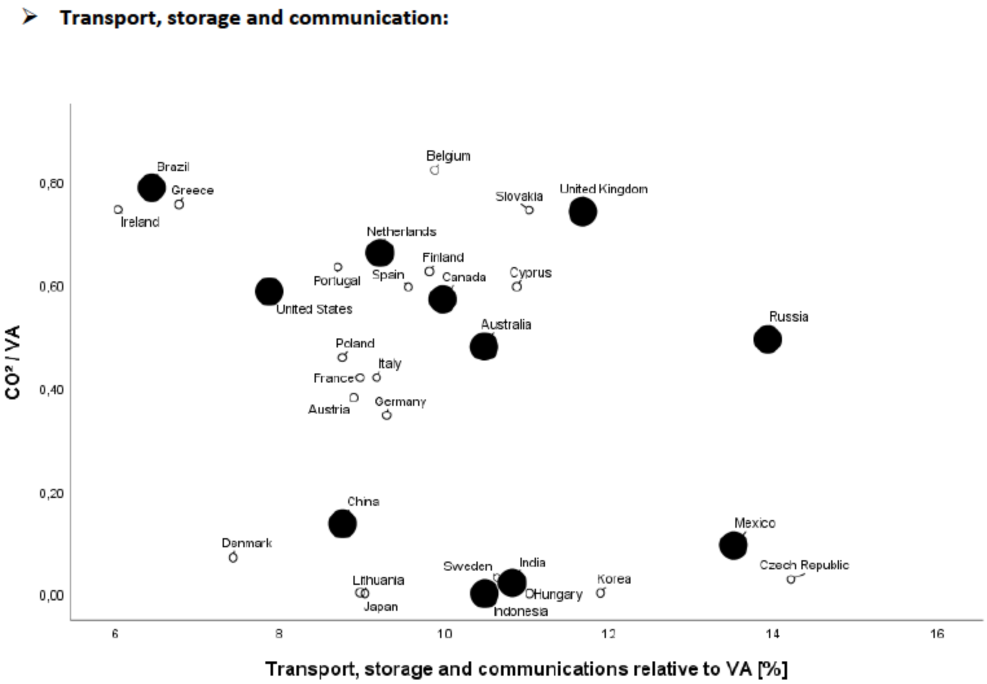

Figure 3B: Relationship between sectorial carbon intensity and the share of sector Value added in GDP.

3 The empirical model

This section first presents the methodology used for estimates at national level, followed by the sectorial approach.

3.1 Country wide estimation

In this section, we outline our empirical procedure. Our aim is to explore the underlying factors that determine the degree to which economies depend on natural resource abundance and analyze the impact of resource abundance on carbon intensity performance. Resource abundance may directly affect CO_2 emissions; but the influence may also be indirect, either through the level of corruption or through environmental policy stringency impact. Our empirical approach allows us to analyze direct and indirect links. To do so, we estimate the following panel data model:

$$\begin{aligned} (CO_2/PIB)_{it} &= \beta_0 + \beta_1 R_{it} + \beta_2 R_{it}^2 + \beta_3' X_{it} + \alpha_i + \nu_t + \varepsilon_{it} \quad (1) \\ i &= 1,..,29\ ;\ t = 1,..,15 \end{aligned}$$

where the variable CO_2/PIB denotes CO_2 emissions measured as emissions per GDP (kg per PPP $ of GDP) in country i at time t. R is the variable which represents natural resources. As explained before, it could be either the percentage of national income from primary commodity exports, the percentage of total exports from primary commodity exports or the natural resources stock. In this paper, we restrict ourselves to the World Bank's natural resources data (Changing Wealth of Nations; World Bank 2011). In fact, we use the Log of the subsoil wealth measure that values (in US$ 2005) the main fuel and non-fuel mineral stocks present in a country. R^2 tries to capture the natural resources non-linear effect on CO_2 intensity. So we expect an overall positive effect of abundance, that can be either a quasi-concave function, if $\beta_1 > 0$ and $\beta_2 \leq 0$ or a U-shaped curve if $\beta_1 < 0$ and $\beta_2 > 0$.

X_{it} is a set of control variables used in the literature to explain the CO_2 intensity. We use 6 main variables which can be divided in two different categories. The first set of controls is comprised of preferences and policy measures; environmental policy stringency (EPS), share of Alternative and nuclear energy in total energy use[3], the level of technology and the level of corruption. The second set include climatic variables (heating degree days and cooling degree days. Finally, α_i is the individual fixed effect that allows to capture the impact of specific unobservable and observable variables that are constant over time for each country. The combination of individual α_i with time fixed effect ν_t avoids any endogeneity issue related to omitted variables. Furthermore, all the variables are in natural logarithm except of corruption.

In order to highlight the concept of carbon curse, we estimate a panel data model. Ideally, the random effect estimator would be the best choice since it exploits both the cross-section and dynamic dimensions of our panel data in an efficient way. However, a robust Hausman test specification rejects it (Wooldridge (2002)). Thus, we use a fixed effect model using within estimator which is consistent even if the fixed effects are correlated with the independent variables. The within estimator corrects for heteroscedasticity and intra-group correlation. However, one might argue that CO_2 emissions are spatially correlated. In order to remove any doubt, we run two well-known tests; Pesaran parametric test for cross-sectional dependence following the methods shown in Pesaran (2004) and Frees semi-parametric test for cross-sectional dependence using Frees' Q distribution (Frees (1995)). Both tests reject the null hypothesis of cross-sectional independence across panel units. Thus, if we have spatially correlated omitted variables and these omitted variables are independent of the included explanatory variables then within coefficient estimates are unbiased but inefficient. In this situation we should allow the error term in equation to be spatially correlated. To do so, we use a non-parametric technique: Driscoll and Kraay's covariance estimator. Driscoll and Kraay (1998) standard

[3] Clean energy is noncarbohydrate energy that does not produce carbon dioxide when generated. It includes hydropower and nuclear, geothermal, and solar power, among others.

errors are robust to very general forms of cross-sectional ("spatial") and temporal dependence when the time dimension becomes large. The results of the various estimation techniques as well as the results of the tests described above are provided in Section 4.

3.2 Industry specific estimation

Once the concept of carbon curse has been confirmed at the macroeconomic level, we use sectorial analysis to disentangle the overall effect of resource endowment on CO_2 emissions. We investigate if fuel rich countries pollute more than fuel poor countries in all sectors of activities. In other words, is there any effect of spreading polluting practices to all sectors of the economy? Obviously, we expect that the level of pollution in the mining sector will be higher in fuel rich than in fuel poor countries, but is it still true for the other sectors? Firstly, we need to distinguish at least two groups of countries: fuel poor and fuel rich countries. To do so, we use the K-means clustering algorithm to find groups which have not been explicitly labeled in the data. The number of groups to find are explicitly chosen by the user. Indeed, in our study, the choice of 2 groups is quite intuitive and relevant given the relative small size of our sample (table 1 indicates the countries of each group). Second, we estimate the following panel data model on each subsample and then compare the results:

$$\begin{aligned}(CO_2/VA)_{ijt} &= \sum_{j=1}^{7} \beta_{1j}(R_{it} * dummy_j) + \beta_2' X_{it} + \beta_3' X_{ijt} + \alpha_i + \delta_j + \theta_{ij} + \delta_{jt} + \nu_t + \varepsilon_{ijt} \qquad (2)\\ i &= 1,..,29\ ;\ j = 1,..,7\ ;\ t = 1,..,15\end{aligned}$$

In the above equation, $(CO_2/VA)_{ijt}$ stands for CO_2 emissions per dollar of value added of sector j in country i at time t, whereas X_{it} is a vector of k observed time-varying exogenous characteristics of country i like EPS, corruption, climatic condition variables (CDD and HDD) and a time fixed effect ν_t. We also include X_{ijt} a vector of k observed time varying exogenous characteristics of sector j in country i like technological level and δ_{jt}. All time-invariant characteristics of the countries and industries are captured by the fixed effect which are, respectively, α_i, δ_j and θ_{ij}. Finally, in order to test if the effect of the resource endowment is different by sector, we introduce an interaction term between natural resource and sectorial dummies variable. To estimate this equation, we use the fixed effect estimator and use the same routine as in the country-wide estimation. Furthermore, all the variables are in natural logarithm except of corruption.

4 Estimation results

We present here the main estimation results obtained by applying the methodology exposed previously.

4.1 Country wide estimation

Table 4 reports the estimation results of both random effects and fixed effects models using OLS, column 1 and 2, respectively. In both models, all of the estimated coefficients which are significant at the 5% level have the expected sign except for the technological variable. The estimated parameters in both models are not significantly different, which is often the case for datasets of comparable dimensions. Table 4 reports also various test results:i) the F-test for individual effects tests the null of $\alpha_i = 0,\ \forall i$ in equation (1); ii) the Breusch-Pagan test for random effects tests the null of $Var(\alpha_i) = 0$ in equation (1); and iii) the Hausman test of fixed effects versus random effects strongly rejects the random effects model. Thus we select the fixed effects model for our analysis. To ensure our estimates we check for cross-sectional correlation. Accordingly, we perform various standard tests for cross-sectional dependence proposed by Pesaran (2004) and Frees (1995) and implemented in STATA by Sarafidis and De Hoyos (2006). Tests results are reported in Table 4 and strongly reject the null hypothesis of cross-sectional independence.

Consequently, we re-estimate the model using Driscoll and Kraay's covariance estimator to account for cross-sectional (spatial) correlation. The estimation results are reported in column (3) of Table 4. The estimated coefficients are exactly the same and now highly significant when we correct for spatial correlation. All else being equal, a rise of 1% in the alternative energy result in 0,13% lower CO_2 intensity. The increase in relative share of alternative energy reflects an increase in cleaner energy, resulting in lower CO_2 intensity. The estimated coefficients on climatic variable (CDD and HDD) show no impact on CO_2 intensity. This result can be explained by the fact that we take the average annual temperatures, which leads to insignificant results. Also, all else equal, an increase of 1% in Environmental Policy Stringency (EPS) results in 0,07% lower CO_2 intensity. This direct effect on CO_2 intensity reflects the impact of new or stricter command and control instruments.[4] In addition, the direct effect of the technology on CO_2 intensity is significantly positive. Previous contributions have yielded mixed results on the technology/CO_2 relationship (for a summary see Lantz and Feng (2006)). We use a general proxy for the technology and we do not specifically consider green technologies. Qualitative results on technology can be explained by the fact that new technologies are not necessarily less emitting than older technologies. This may explain why technological development impact

[4] The results indicate that there is no significant change for all variables when using lagged (past values) of the EPS variable. The results for the lagged EPS variable are qualitatively identical and quantitatively similar to those of the reference model. Results are available upon request.

positively impact CO_2 intensity.

Table 4: OLS estimation results of random effect and fixed effect models

Model	Random effects (1)		Fixed effects (2)		Fixed effects Driscoll-Kraay estimator (3)	
Abundance	-0.145***	(-3.32)	-0.134*	(-1.82)	-0.134***	(-3.76)
Abundance^2	0.003***	(3.28)	0.003*	(1.72)	0.003***	(3.77)
Alternative Energy	-0.130***	(-7.73)	-0.134***	(-3.68)	-0.134***	(-5.90)
Stringency	-0.071***	(-4.85)	-0.070**	(-2.38)	-0.070***	(-3.19)
Heating DD	0.009	(0.63)	-0.001	(-0.06)	-0.001	(-0.03)
Cooling DD	0.014	(1.01)	0.012	(1.05)	0.012	(0.68)
Technological level	0.082***	(7.75)	0.087**	(2.75)	0.087***	(14.03)
Corruption	0.040**	(1.99)	0.053	(1.66)	0.054	(1.58)
Constant	-0.260	(0.49)	-0.333	(-0.42)	-0.333	(-0.67)
			F-test for individual effects			
F(28,350)			278.57 [0.000]			
			Breusch Pagan test for random effects			
$\chi^2_{(1)}$			2004.49 [0.000]			
			Hausman test of fixed effects versus random effects			
$\chi^2_{(14)}$			445..447 [0.000]			
			Pesaran's test of cross sectional independence			
			-3.131 [0.0017]			
			Frees' test of cross sectional independence			
			5.303 [0.000]			

Note: Standard errors are in (); *, ** and *** refer respectively to the 10%, 5% and 1% significance levels; P-values are in [ ].

Finally, our results clearly show the existence of a U-shaped curve at country level. This means that the same level of CO_2 intensity can be achieved, all else being equal, by a resource-poor country as well as a resource-rich country. In other words, there is a turning point in the relationship between CO_2 per unit of GDP and abundance, such that before this point, the elasticity is negative while it is positive beyond. Carbon curse is therefore a somewhat more complex phenomenon than Friedrichs and Inderwildi (2013) suggests and does not affect countries with few resources. Our study confirms that it is very difficult to avoid the carbon curse, and perhaps even more difficult than avoiding the resource curse in general. Indeed, our sample allows us to confirm the validity of carbon curse even though it does not include countries facing the resource curse.

4.2 Industry country specific estimation

To try to explain the complexity of the carbon curse highlighted at national level, we propose a sectorial analysis of the relationship between CO2 intensity and our different explanatory variables. To do this, we group the countries according to their level of abundance using the K-means method. The results are shown in Table 5.[5]

Table 5: Estimation results of the fixed effect model

	Fixed effects			
	Resources rich		Resources poor	
Agriculture_abund	0.111	(1.02)	-0.057**	(-2.51)
Transport_abund	0.508***	(3.45)	-0.093***	(-4.14)
Manufacturing_abund	0.509***	(5.15)	-0.052***	(-3.61)
Construction_abund	-0.230	(-1.42)	0.055**	(2.59)
Electricity_abund	0.435***	(2.96)	0.082***	(3.17)
Mining_abund	0.859***	(4.96)	0.070	(1.05)
Service_abund	0.562***	(4.13)	0.011	(0.74)
Stringency	-0.046**	(-2.11)	-0.011	(-0.42)
Corruption	0.049	(1.10)	-0.002	(-0.07)
Heating DD	0.018	(0.24)	0.386***	(3.60)
Cooling DD	-0.023	(-0.83)	0.012	(0.72)
Technological level	-0.054	(-1.36)	0.039	(1.43)

Note: Standard errors are in () ; *, ** and *** refer respectively to the 10%, 5% and 1% significance levels.

We show that in resource-rich countries, the sector most sensitive to abundance is obviously the mining sector, while abundance has no impact on this sector in resource-poor countries. In resource-rich countries, apart from the construction and agriculture sectors, abundance always has a positive and very significant impact on emissions rates. A spreading effect of the influence of abundance is thus occurring towards less resource-intensive sectors. In resource-poor countries, on the other hand, the effect is more ambiguous because in agriculture, transport and manufacturing sectors, abundance plays a negative role. The Environmental Stringency significantly reduces CO_2 intensity but only in resource-rich countries.

5 Discussion and Conclusion

In this article, we have empirically assessed the validity of the carbon curse assumption. We demonstrate that countries rich in coal, oil and gas emit more CO_2 per unit of GDP as countries where fossil fuels are relatively rare. This relationship is U-shaped, i.e. there is a turning point in the relationship between CO_2 per unit of GDP and abundance, such that before this point, the elasticity is negative while it is positive beyond. Carbon curse is therefore a somewhat more complex phenomenon. We then test the consequences of abundance on the sectorial emissions for two groups of countries, depending on their resource endowments.

[5] All the variables in Table 5 that end with "_abund" correspond to the dummy variable ($R_{it}\_dummy_j$) in equation (2). The related estimated coefficient capture the average impact of abundance on CO_2 sectorial intensity across sectors.

We estimate the relationship between sectorial CO_2 emissions per value added, abundance, technology level, environmental policy stringency, corruption, the energy mix, cooling and heating degree days. We confirm that a country rich in fossil and mineral resources pollutes more in resource-related sectors, but we find also that CO_2 intensity is positively and highly impacted in all other sectors of these countries, even in the service sectors. We conclude that there is a spreading process of the polluting practices in resource rich countries, that is explained not only by a composition effect, but also a scale effect (and potentially a technological effect). Further research may address the potential links between these pollution mechanisms and the characteristics of the resources (natural gas, non-conventional oil, coal, mineral resources, etc.).

References

Adani, Riccardo Marchi, Ricciuti, Roberto, et al. . (2014). The resource curse, rule of law and accountability in African countries: a dynamic panel analys. *Economics Bulletin*, 34(3), 1905–1916.

Alexeev M. and Conrad R. (2009). The Elusive Curse of Oil, *The Review of Economics and Statistics*, MIT Press, vol. 91(3), pages 586-598, August.

Badeeb, R. A., Lean, H. H., & Clark, J. (2017). The evolution of the natural resource curse thesis: A critical literature survey. *Resources Policy*, 51, 123-134.

Brunnschweiler, Christa N, & Bulte, Erwin H. (2008). The resource curse revisited and revised: A tale of paradoxes and red herrings. *Journal of environmental economics and management*, 55(3), 248–264.

Bruno, Michael, & Sachs, Jeffrey. (1982). Energy and resource allocation: A dynamic model of the "Dutch Disease". *The Review of Economic Studies*, 49(5), 845–859.

de Bruyn, S.M., Van den Bergh, J.C.J.M., Opschoor, J.B., (1998). Economic growth and emissions: reconsidering the empirical basis of environmental Kuznets curves. *Ecological Economics*, 25, 161–175.

Corden, Warner Max. (1984). Booming sector and Dutch disease economics: survey and consolidation. *Oxford economic Papers*, 359–380.

Ding N., Field B.C. (2005), Natural resource abundance and economic growth, *Land Economics* 81 (3), 496–502.

Driscoll, J. C., and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of economics and statistics*, 80(4), 549-560.

Frees, E.W. (1995) Assessing cross-sectional correlations in panel data, *Journal of Econometrics*, 64, 393-414.

Friedrichs, J., & Inderwildi, O. R. (2013). The carbon curse: Are fuel rich countries doomed to high CO 2 intensities?. *Energy Policy*, 62, 1356-1365.

Fuinhas, J. A., Marques, A. C., & Couto, A. P. (2015). Oil rents and economic growth in oil producing countries: evidence from a macro panel. *Economic Change and Restructuring*, 48(3-4), 257-279.

Galeotti M. (2007). Economic growth and the quality of the environment: Taking stock, *Environment, Development and Sustainability*, 9(4), 427-454.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The quarterly journal of economics*, 110(2), 353-377.

Gylfason, Thorvaldur. (2001). Natural resources, education, and economic development. European economic review, 45(4), 847–859.

Hartwell, C. A. (2016). The institutional basis of efficiency in resource-rich countries. *Economic Systems*, 40(4), 519-538.

Hettige, H., Mani, M., Wheeler, D., (1999). Industrial pollution in economic development: Kuznets revisited. In P. (Ed.), “Trade, Global Policy and the Environment”, World Bank Discussion Papers, Vol. 402. Washington DC: World Bank.

Holtz-Eakin, D., Selden, T.M. (1995). Stoking the fires? CO2 emissions and economic growth. *Journal of Public Economics*, 57, 85-101.

Jensen, Nathan, & Wantchekon, Leonard. (2004). Resource wealth and political regimes in Africa. *Comparative political studies*, 37(7), 816–841.

Kaufmann D., Kraay A. and M. Mastruzzi (2010). The Worldwide Governance Indicators : A Summary of Methodology, Data and Analytical Issues. World Bank Policy Research Working Paper No. 5430. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1682130

Krugman, Paul. (1987). The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher: Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics*, 27(1), 41–55.

Lantz, V. and Q. Feng, (2006). Assessing income, population, and technology impacts on co2 emissions in canada: Where’s the EKC? *Ecological Economics*, 57 (2), 229–238.

Matsen, Egil, & Torvik, Ragnar. (2005). Optimal Dutch Disease. *Journal of Development Economics*, 78(2), 494–515.

Mirnezami, S. R. (2015). Do Oil-Producing Countries Have Normal Oil Overconsumption? An Investigation of Economic Growth and Energy Subsidies. *AIMS Energy*, 3(3), 267-283.

Panayotou, T., (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. Working Paper WP238 Technology and Employment Programme, Geneva: International Labor Office.

Pesaran, M.H. (2004) General diagnostic tests for cross section dependence in panels, Cambridge Working Papers in Economics, 0435, University of Cambridge.

Puyana-Mutis, A., Santillán-Vera, M., & Pérez-Guzmán, K. (2014). The Relation between oil production and the CO_2 emissions of the manufacturing sector: a decomposition analysis of Mexico's industry from 1970-2010. *European Scientific Journal*, ESJ, 10(10).

Robinson, James A, Torvik, Ragnar, & Verdier, Thierry. (2006). Political foundations of the resource curse. *Journal of Development Economics*, 79(2), 447–468.

Roca, J., Padilla, E., Farré, M., Galletto, V., (2001). Economic growth and atmospheric pollution in Spain: Discussing the environmental Kuznets curve hypothesis. *Ecological Economics*, 39, 85-99.

Sachs, Jeffrey D, & Warner, Andrew M. (1995). Natural resource abundance and economic growth. Tech. rept. National Bureau of Economic Research.

Sachs, Jeffrey D, & Warner, Andrew M. (1999). The big push, natural resource booms and growth. *Journal of Development Economics*, 59(1), 43–76.

Sarafidis V. and De Hoyos R.E. (2006). On testing for cross sectional dependence in panel data models, mimeo, University of Cambridge.

Selden, T.M., Song, D. (1994). Environmental quality and development: is there a Kuznets curve for air pollution estimates. *Journal of Environmental Economics and Management*. 27, 147–162.

Shafik, N., Bandyopadhyay, S., (1992). Economic growth and environmental quality: time series and cross-country evidence. Background Paper for World Development Report 1992, World Bank, Washington, DC.

Torras, M., Boyce, J.K., (1998). Income, inequality and pollution: a reassessment of the environmental Kuznets curve. *Ecological Economics*. 25, 147–160.

Torvik, Ragnar. (2001). Learning by doing and the Dutch disease. *European Economic Review*, 45(2), 285–306.

Van der Ploeg, F. (2011). Natural resources: Curse or blessing?. *Journal of Economic Literature*, 49(2), 366-420.

Van der Ploeg, Frederick, & Poelhekke, Steven. (2009). Volatility and the natural resource curse. Oxford economic papers.

Van der Ploeg, F., & Poelhekke, S. (2017). The impact of natural resources: Survey of recent quantitative evidence. *The Journal of Development Studies*, 53(2), 205-216.

Wooldridge, J.M. (2002). Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: MIT Press.

Appendix

Table 6: Explanatory variables: details and sources

Variable	Units of measurement	Source
CO_2 emissions macro et micro	carbon dioxide (CO_2) emission in kilograms per US$ of GDP (2011 Purchasing Parity Power)	http://databank.worldbank.org/data/reports.aspx?source=2&type=metadata&series=EN.ATM.CO2E.PP.GD.KD
Resource abundance	2005 US$	https://data.worldbank.org/data-catalog/wealth-of-nations
Heating degree days (HDD) Cooling degree day (CDD)	Temperature reference: 18°C and frequency of 6hrs	https://www.kapsarc.org/research/projects/global-degree-days-database/
Environmental Policy Stringency index (EPS)	OECD Environmental Policy Stringency Index: from 0 (not stringent) to 6 (highest degree of stringency)	https://stats.oecd.org/Index.aspx?DataSetCode=EPS
Technology level	Macro level: number of filed patents in a national patent authority from World Intellectual Property Organization (WIPO)	https://data.worldbank.org/indicator/IP.PAT.RESD
	Sector level: high-skilled working hours divided by total working hours	http://www.wiod.org/database/seas13
Alternative energy use	Renewable and nuclear energy (% of total energy use)	https://data.worldbank.org/indicator/EG.USE.COMM.CL.ZS
Corruption	Index of governance performance: from -2.5 (weak) to 2.5 (strong)	Kaufmann, Kraay and Mastruzzi (2010)

Table 7: OLS estimation results of random effect and fixed effect models: Dependent variable CO2 per capita

Model	Random effects		Fixed effects		Fixed effects	
					Driscoll-Kraay estimator	
Abundance	-0.141***	(-3.73)	-0.141*	(-1.90)	-0.141**	(-2.52)
$Abundance^2$	0.003***	(3.43)	0.003*	(1.80)	0.003**	(2.39)
GDP_capita(PPP)	0.590***	16.06	0.540***	7.48	0.540***	(7.22)
Alternative Energy	-0.126***	(-7.73)	-0.130***	(-3.49)	-0.130***	(-7.68)
Stringency	-0.480***	(-3.80)	-0.045**	(-2.51)	-0.045***	(-3.32)
Heating DD	0.016	(1.26)	0.0003	(-0.03)	0.0003	(0.01)
Cooling DD	0.006	(0.51)	0.009	(0.75)	0.009	(0.90)
Technological level	0.13***	(12.99)	0.142***	(5.80)	0.142***	(12.06)
Corruption	0.064***	(3.61)	0.059**	(2.55)	0.059**	(2.32)
Constant	-3.48***	(-6.43)	-3.038***	(-3.40)	-3.038***	(-4.54)
			F-test for individual effects			
F(28,349)			385.35 [0.000]			
			Breusch Pagan test for random effects			
$\chi^2_{(1)}$			2027.73 [0.000]			
			Hausman test of fixed effects versus random effects			
$\chi^2_{(14)}$			455.203 [0.000]			
			Pesaran's test of cross sectional independence			
			-2.459[0.0017]			
			Frees' test of cross sectional independence			
			4.563[0.000]			

Note: Standard errors are in (); *, ** and *** refer respectively to the 10%, 5% and 1% significance levels; P-values are in [ ].